US010489936B1

(12) **United States Patent**
Zafar et al.

(10) **Patent No.: US 10,489,936 B1**
(45) **Date of Patent: Nov. 26, 2019**

(54) **SYSTEM AND METHOD FOR LOSSY IMAGE AND VIDEO COMPRESSION UTILIZING A METANETWORK**

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **16/413,770**

(22) Filed: **May 16, 2019**

Related U.S. Application Data

(63) Continuation-in-part of application No. 16/397,725, filed on Apr. 29, 2019, now Pat. No. 10,373,300.

(51) **Int. Cl.**

G06K 9/00	(2006.01)
G06T 9/00	(2006.01)
G06T 3/40	(2006.01)
G06N 20/20	(2019.01)
G06N 3/08	(2006.01)
G06N 3/04	(2006.01)
G06T 5/20	(2006.01)

(52) **U.S. Cl.**
CPC ***G06T 9/002*** (2013.01); ***G06N 3/0454*** (2013.01); ***G06N 3/08*** (2013.01); ***G06N 20/20*** (2019.01); ***G06T 3/4046*** (2013.01); ***G06T 3/4084*** (2013.01); ***G06T 5/20*** (2013.01)

(58) **Field of Classification Search**
None
See application file for complete search history.

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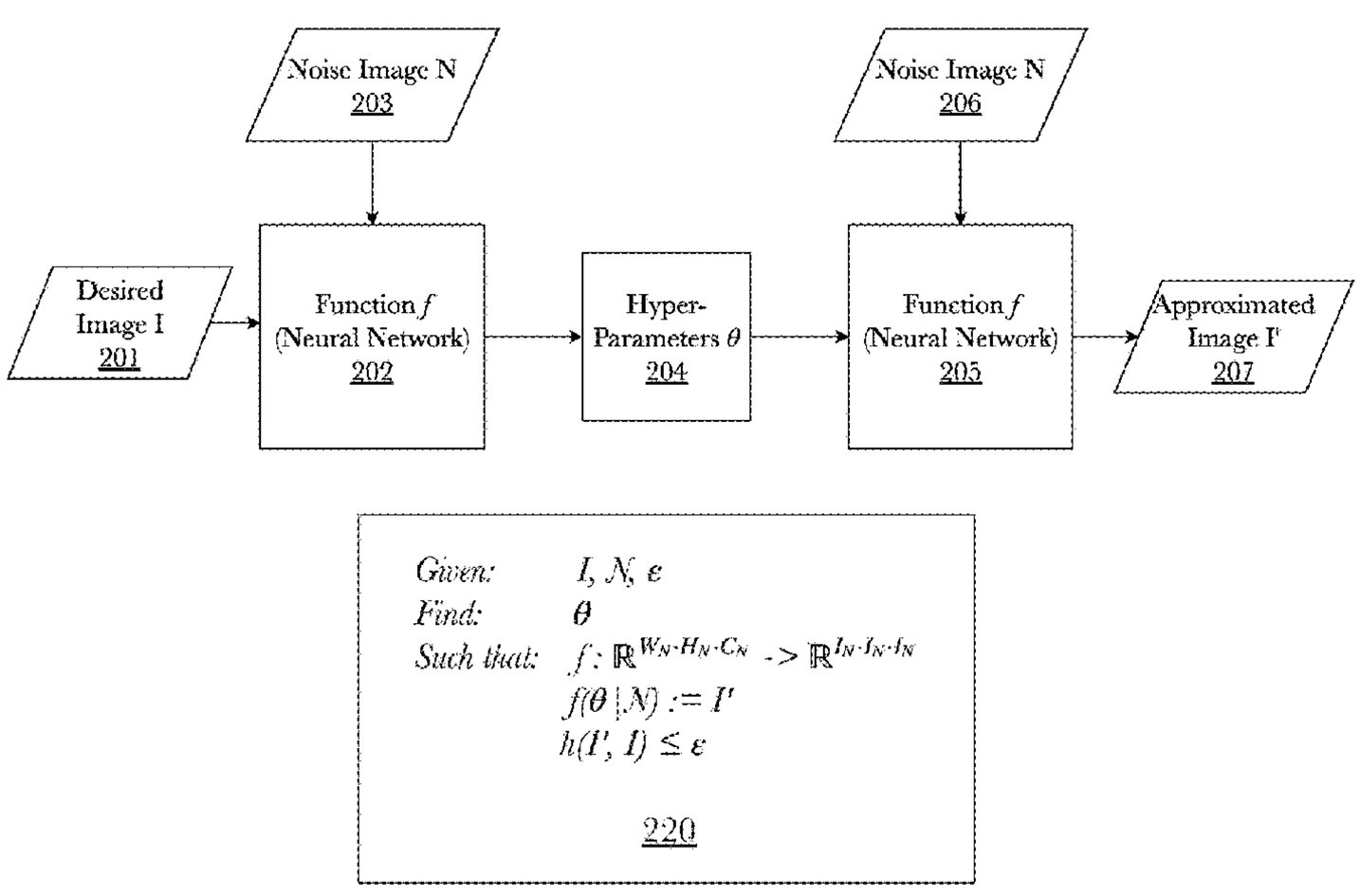
Primary Examiner — Shervin K Nakhjavan
(74) *Attorney, Agent, or Firm* — Brian R. Galvin; Galvin Patent Law, LLC

(57) **ABSTRACT**

A system and method for lossy image and video compression that utilizes a metanetwork to generate a set of hyper-parameters necessary for an image encoding network to reconstruct the desired image from a given noise image.

8 Claims, 24 Drawing Sheets



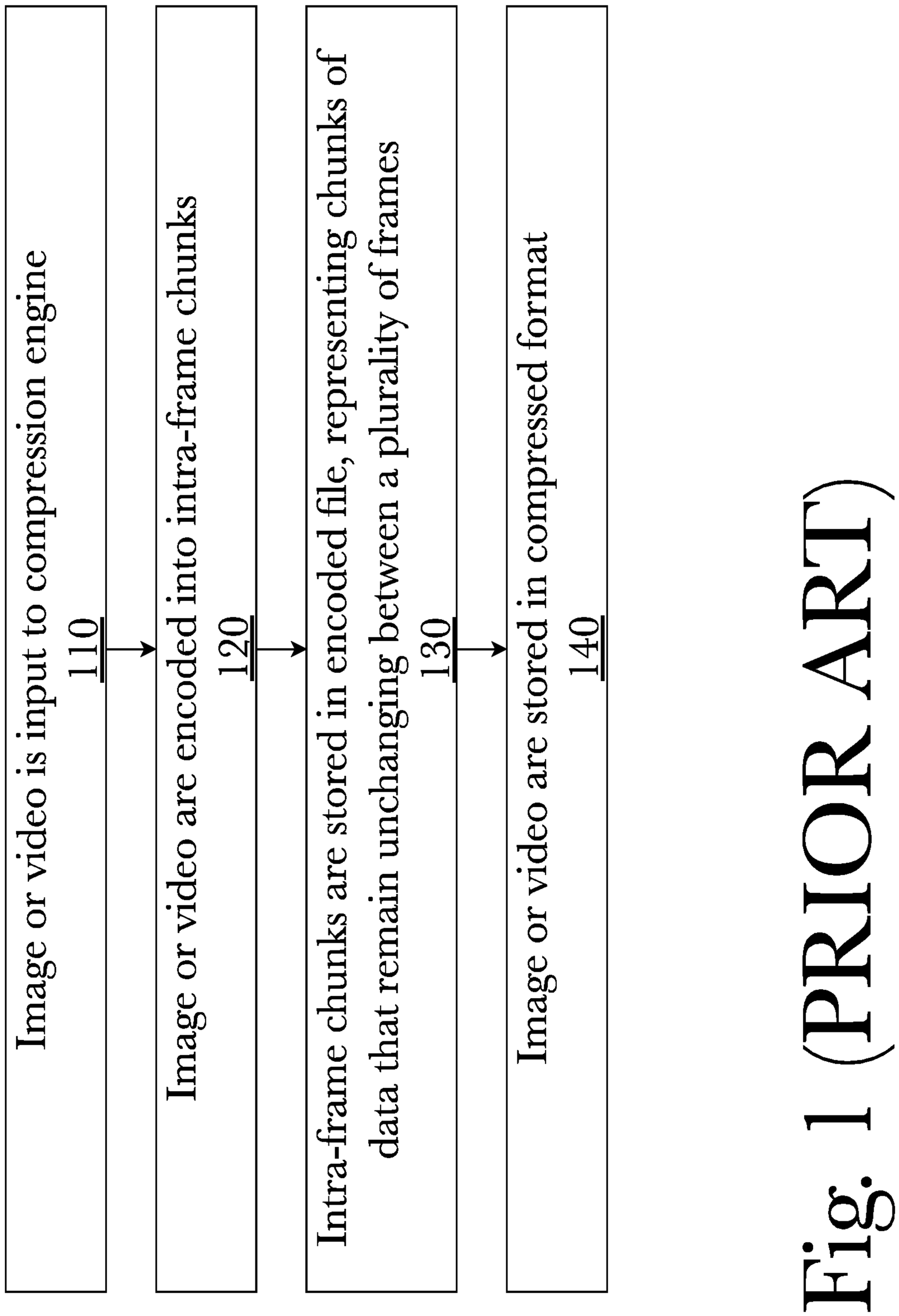


Fig. 1 (PRIOR ART)

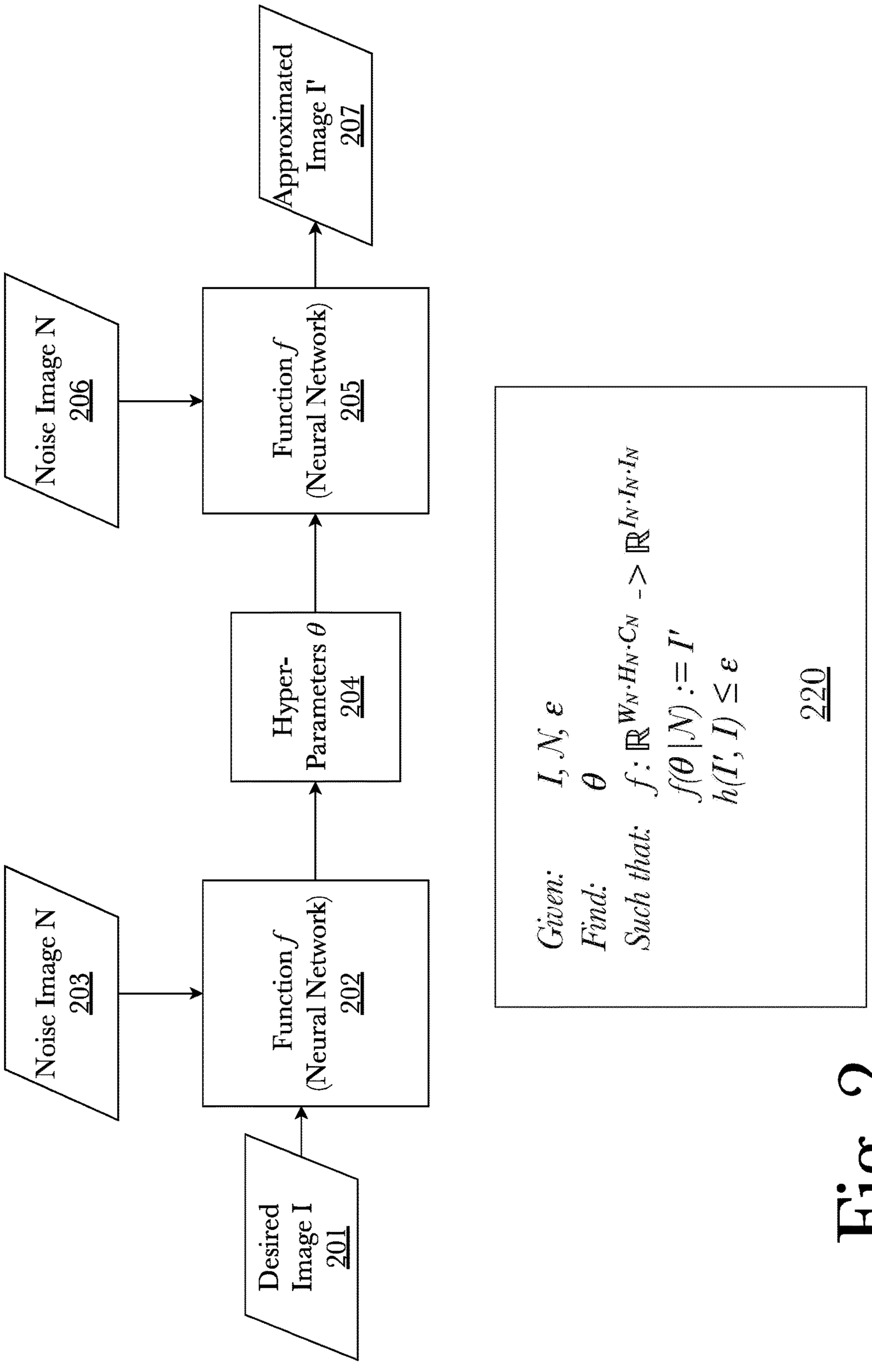

Noise Image N
203
Function f
(Neural Network)
202
Desired
Image I
201
Hyper-
Parameters θ
204
Function f
(Neural Network)
205
Noise Image N
206
Approximated
Image I'
207
Given: I, N, ε
Find: θ
Such that: $f: \mathbb{R}^{W_N \cdot H_N \cdot C_N} -> \mathbb{R}^{I_N \cdot I_N \cdot I_N}$
$f(\theta | N) := I'$
$h(I', I) \leq \varepsilon$
220

Fig. 2

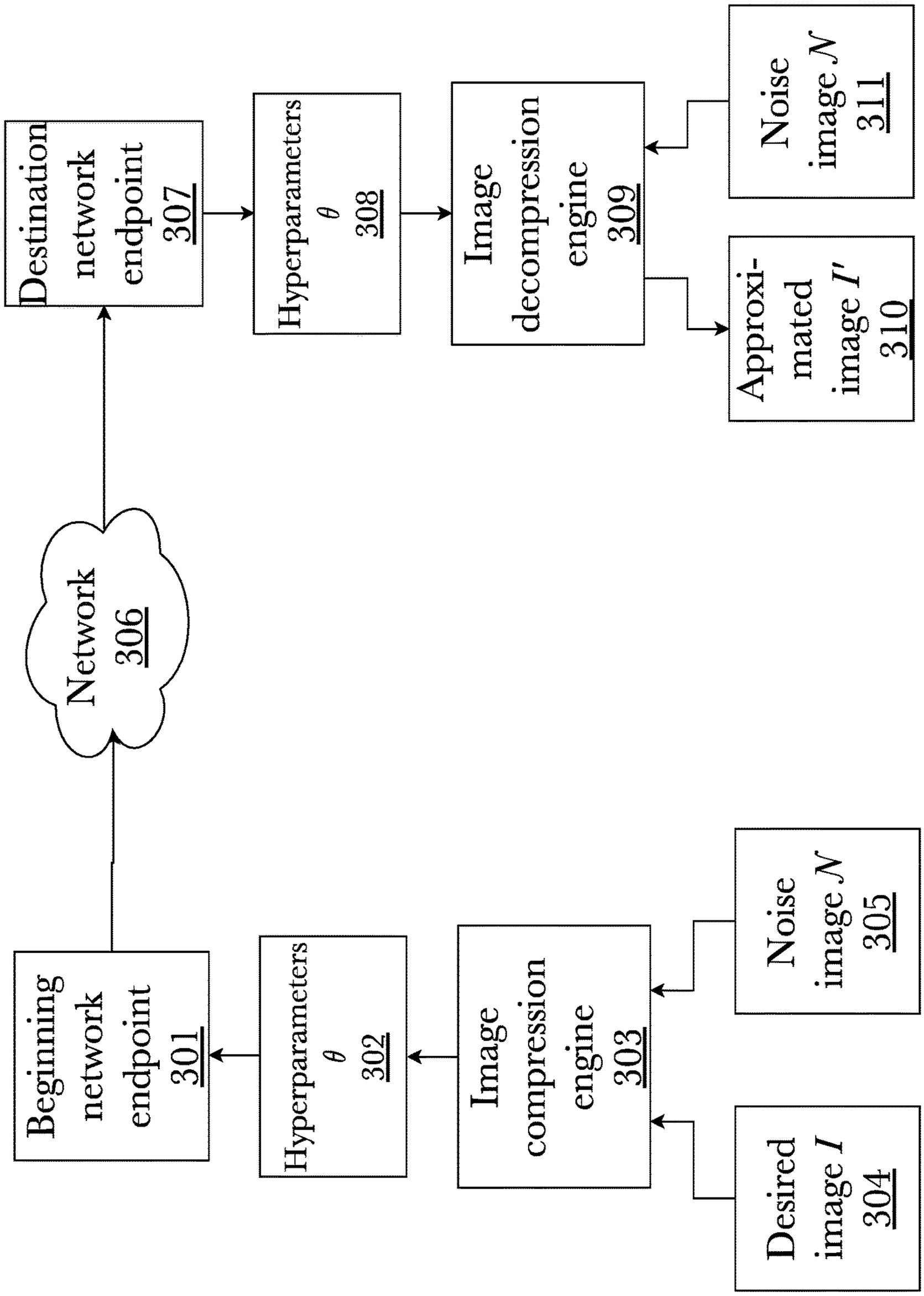

Beginning network endpoint 301
Hyperparameters θ 302
Image compression engine 303
Desired image I 304
Noise image N 305
Network 306
Destination network endpoint 307
Hyperparameters θ 308
Image decompression engine 309
Approximated image I' 310
Noise image N 311

Fig. 3

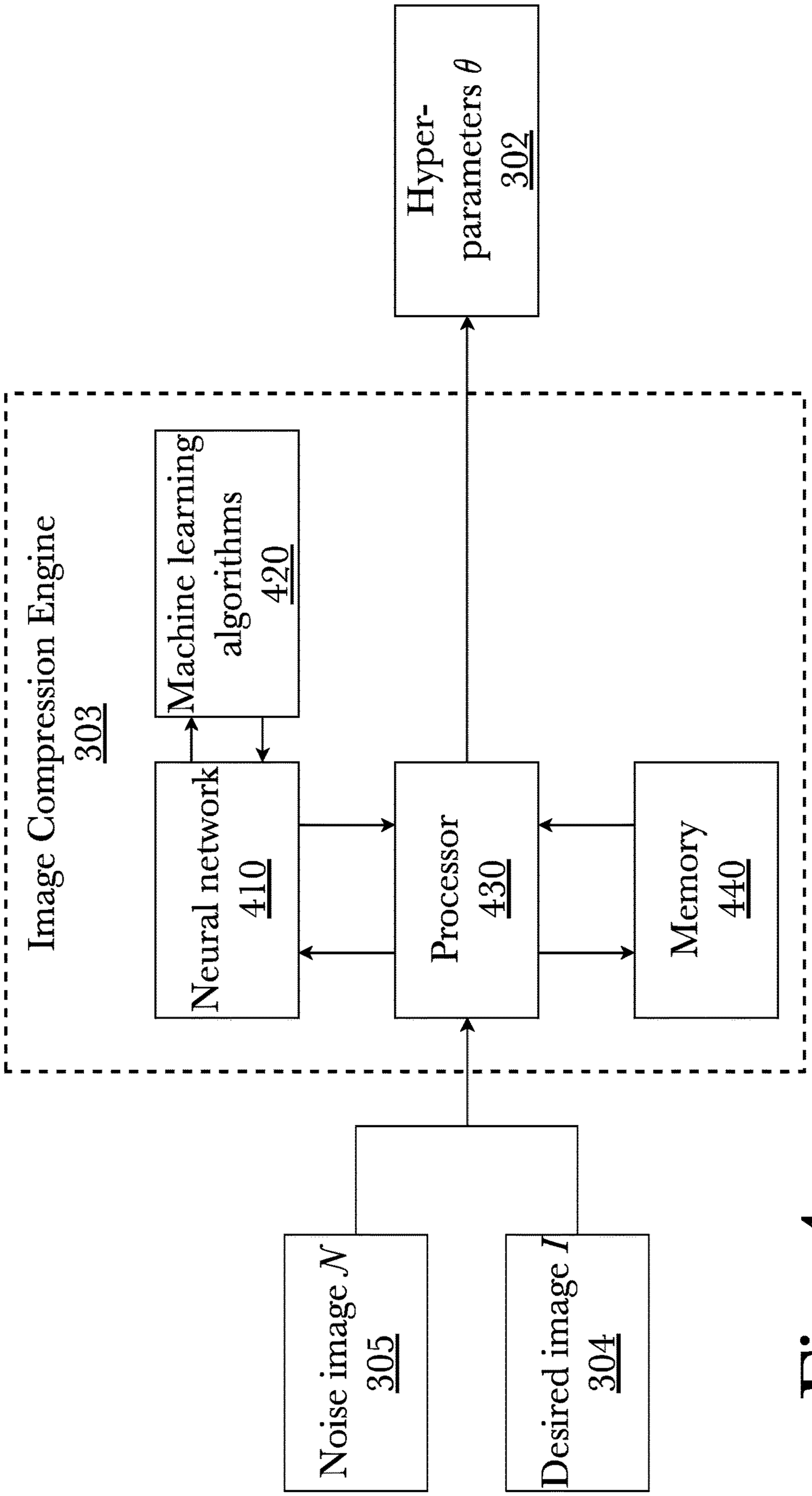

Hyper-parameters θ 302
Image Compression Engine 303
Machine learning algorithms 420
Neural network 410
Processor 430
Memory 440
Noise image N 305
Desired image I 304

Fig. 4

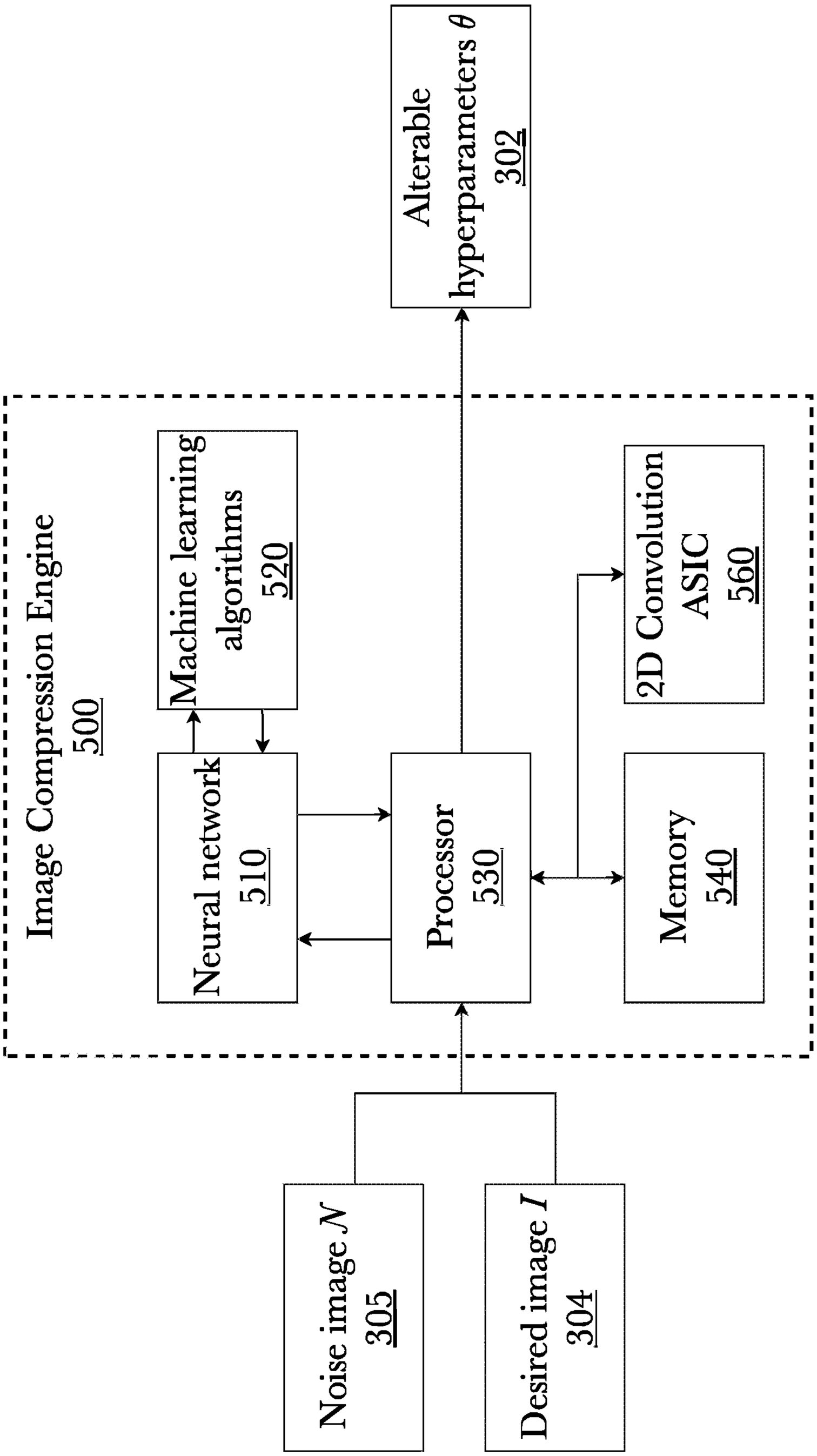

Alterable hyperparameters θ 302
Image Compression Engine 500
Machine learning algorithms 520
Neural network 510
Processor 530
2D Convolution ASIC 560
Memory 540
Noise image N 305
Desired image I 304

Fig. 5

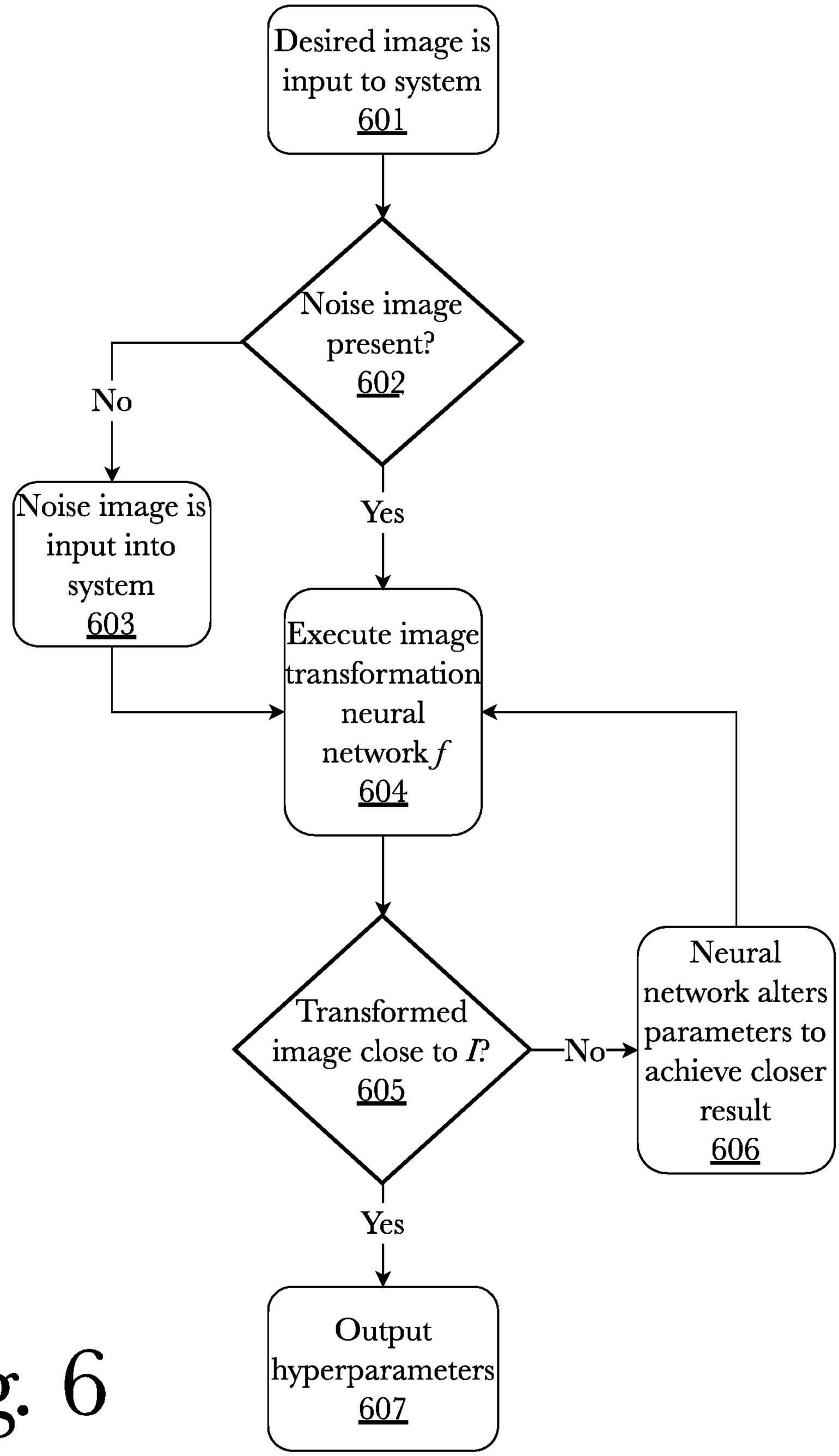

Desired image is input to system
601
Noise image present?
602
No
Noise image is input into system
603
Yes
Execute image transformation neural network *f*
604
Transformed image close to *I*?
605
No
Neural network alters parameters to achieve closer result
606
Yes
Output hyperparameters
607

Fig. 6

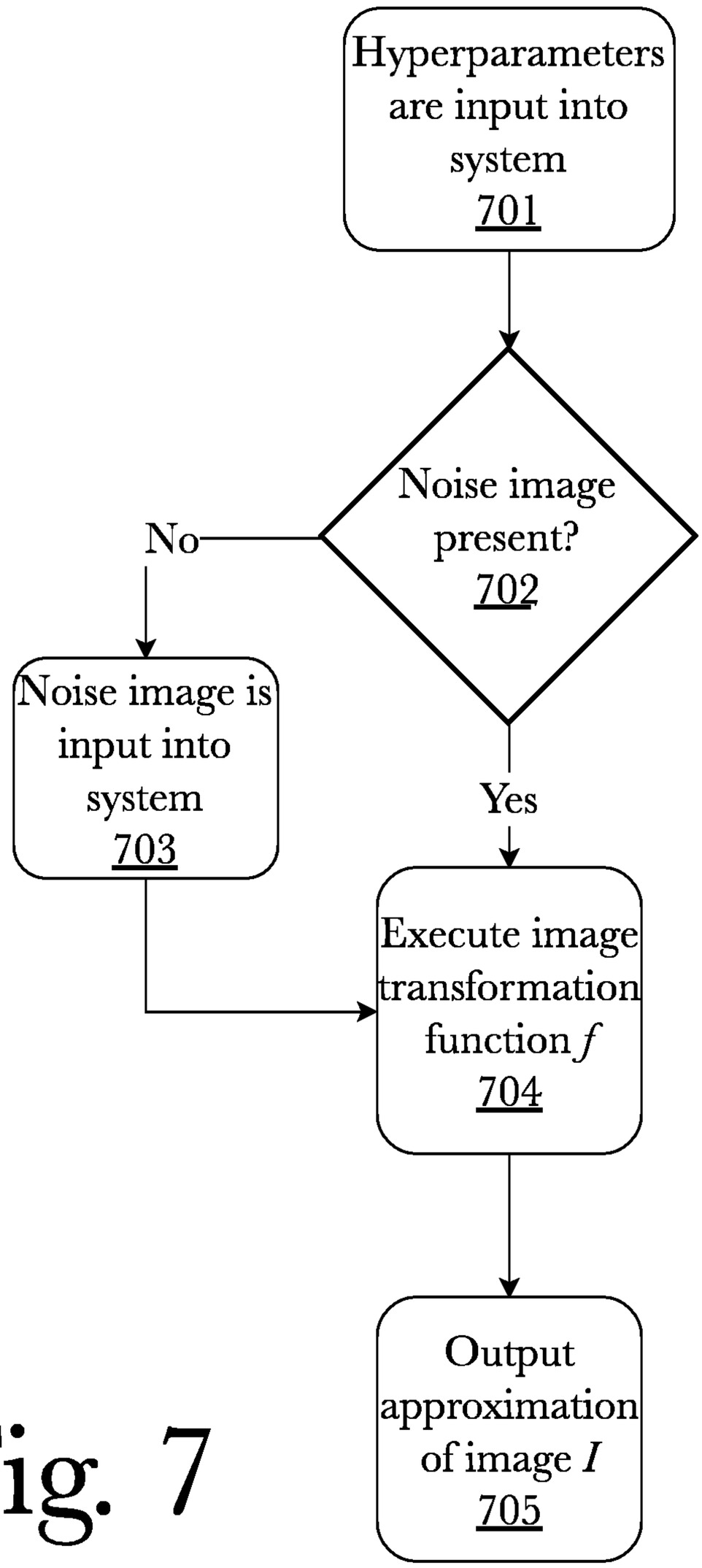

Hyperparameters are input into system
701
Noise image present?
702
No
Yes
Noise image is input into system
703
Execute image transformation function *f*
704
Output approximation of image *I*
705

Fig. 7

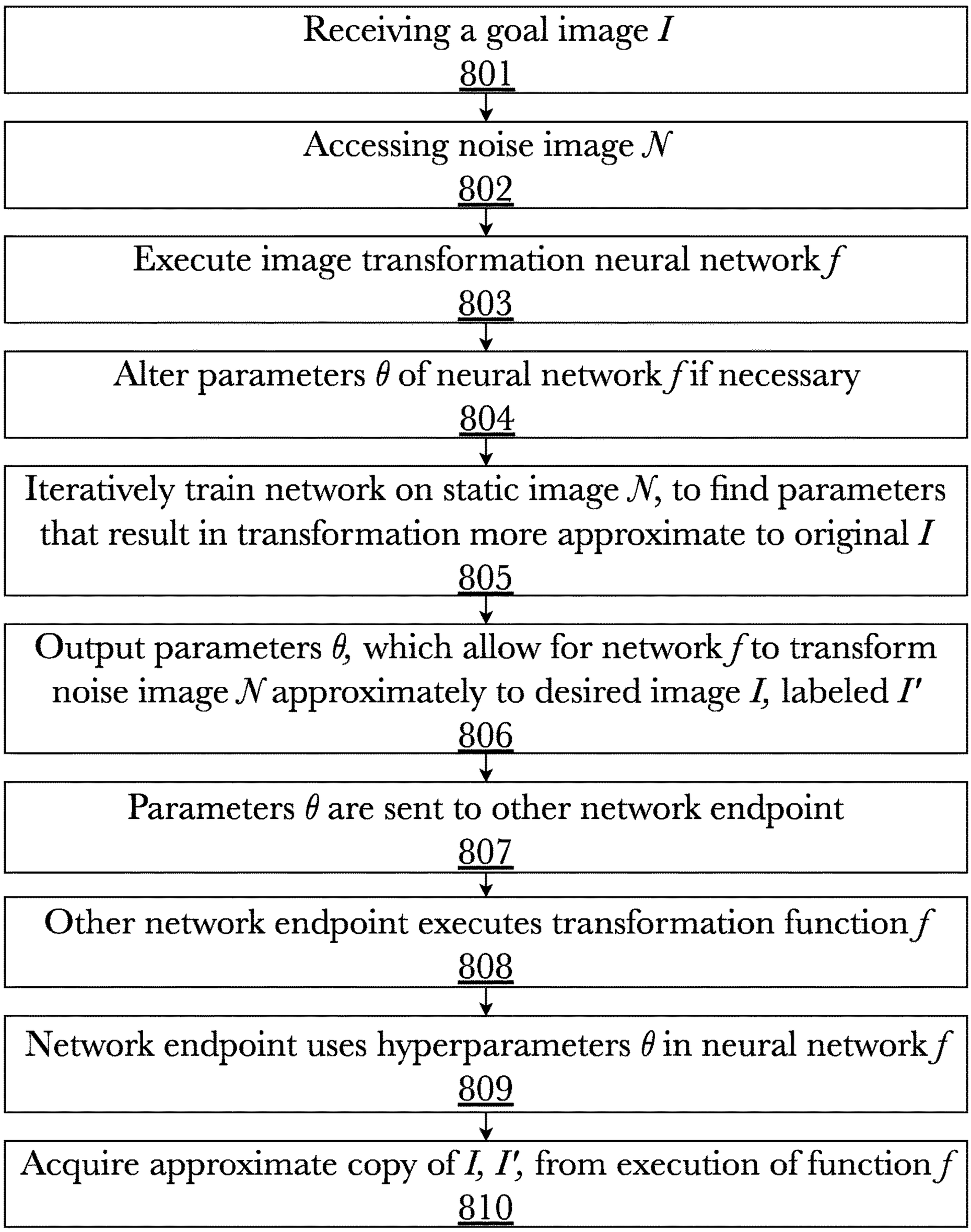

Receiving a goal image I
801
Accessing noise image $\mathcal{N}$
802
Execute image transformation neural network f
803
Alter parameters θ of neural network f if necessary
804
Iteratively train network on static image $\mathcal{N}$, to find parameters that result in transformation more approximate to original I
805
Output parameters θ, which allow for network f to transform noise image $\mathcal{N}$ approximately to desired image I, labeled I'
806
Parameters θ are sent to other network endpoint
807
Other network endpoint executes transformation function f
808
Network endpoint uses hyperparameters θ in neural network f
809
Acquire approximate copy of I, I', from execution of function f
810

Fig. 8

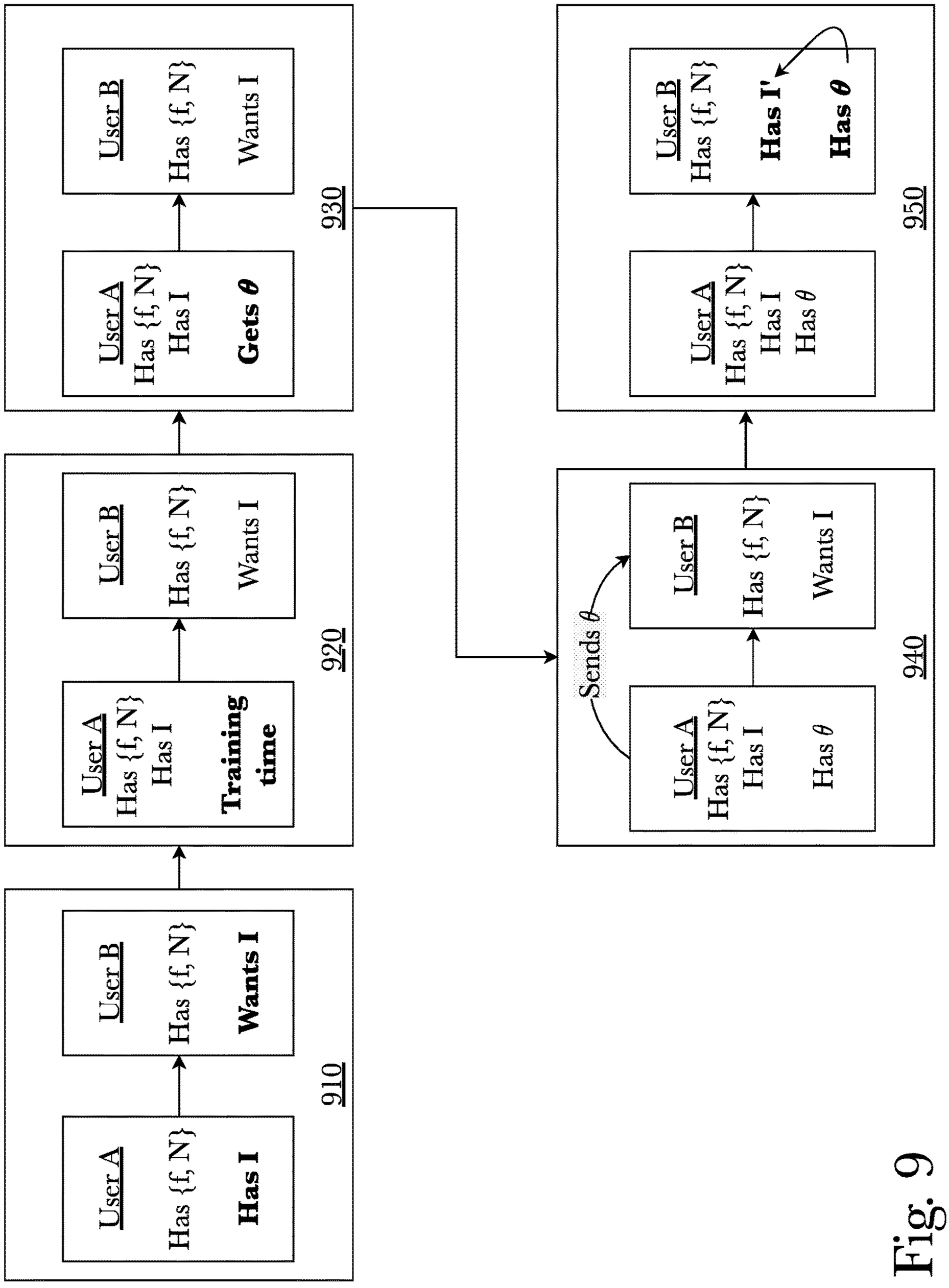
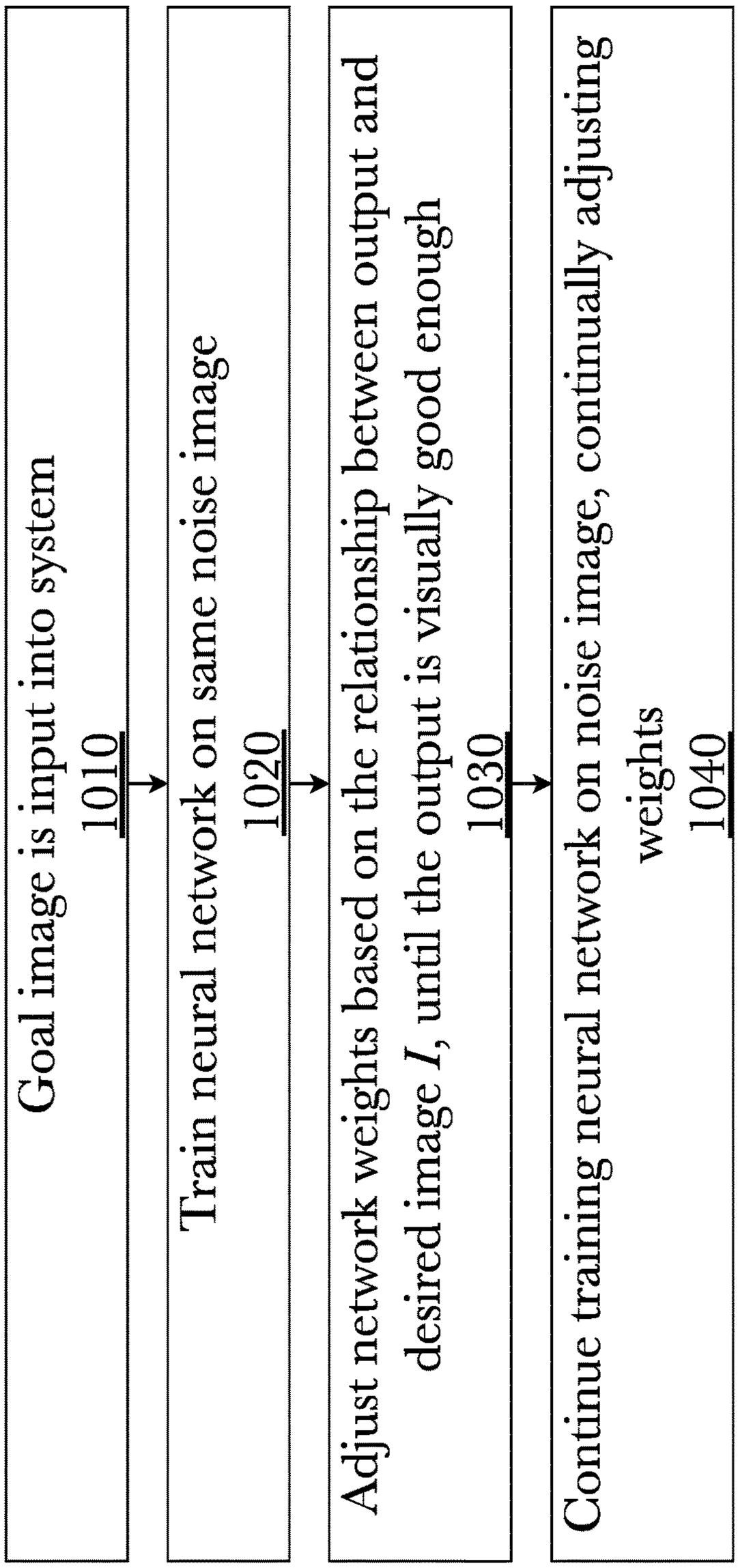

User A
Has {f, N}
Has I
Has θ
User B
Has {f, N}
Wants I
950
940
Sends θ
User A
Has {f, N}
Has I
Gets θ
User B
Has {f, N}
Wants I
920
User A
Has {f, N}
Has I
Training time
User B
Has {f, N}
Wants I
910
User A
Has {f, N}
Has I
User B
Has {f, N}
Wants I

Fig. 9



	Dataset	Input	Weights
Traditional Neural Network:	Huge	Flexible	Fixed
Proposed Neural Network:	One image	Fixed	Flexible

Fig. 10

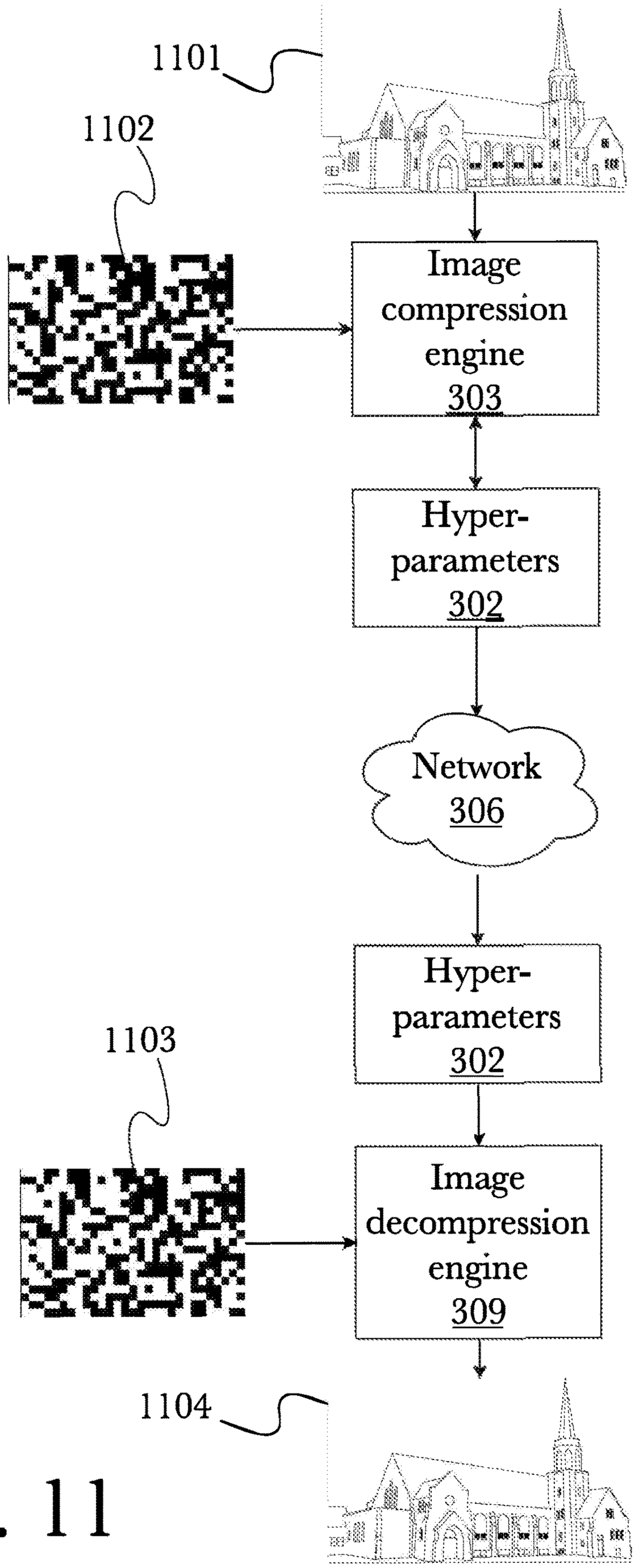

1101
1102
Image compression engine 303
Hyper-parameters 302
Network 306
Hyper-parameters 302
1103
Image decompression engine 309
1104

Fig. 11

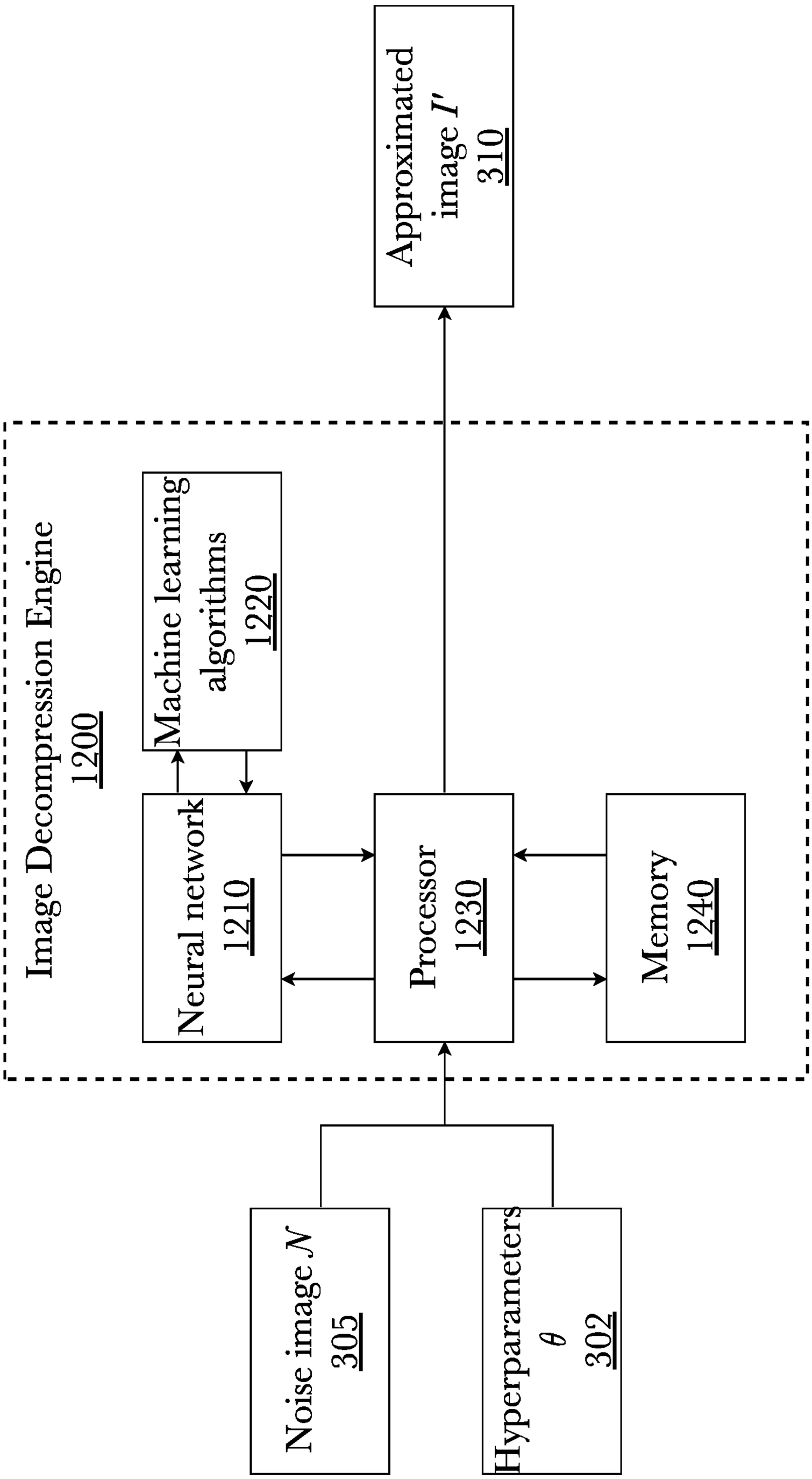

Approximated image I' 310
Image Decompression Engine 1200
Machine learning algorithms 1220
Neural network 1210
Processor 1230
Memory 1240
Noise image N 305
Hyperparameters θ 302

Fig. 12

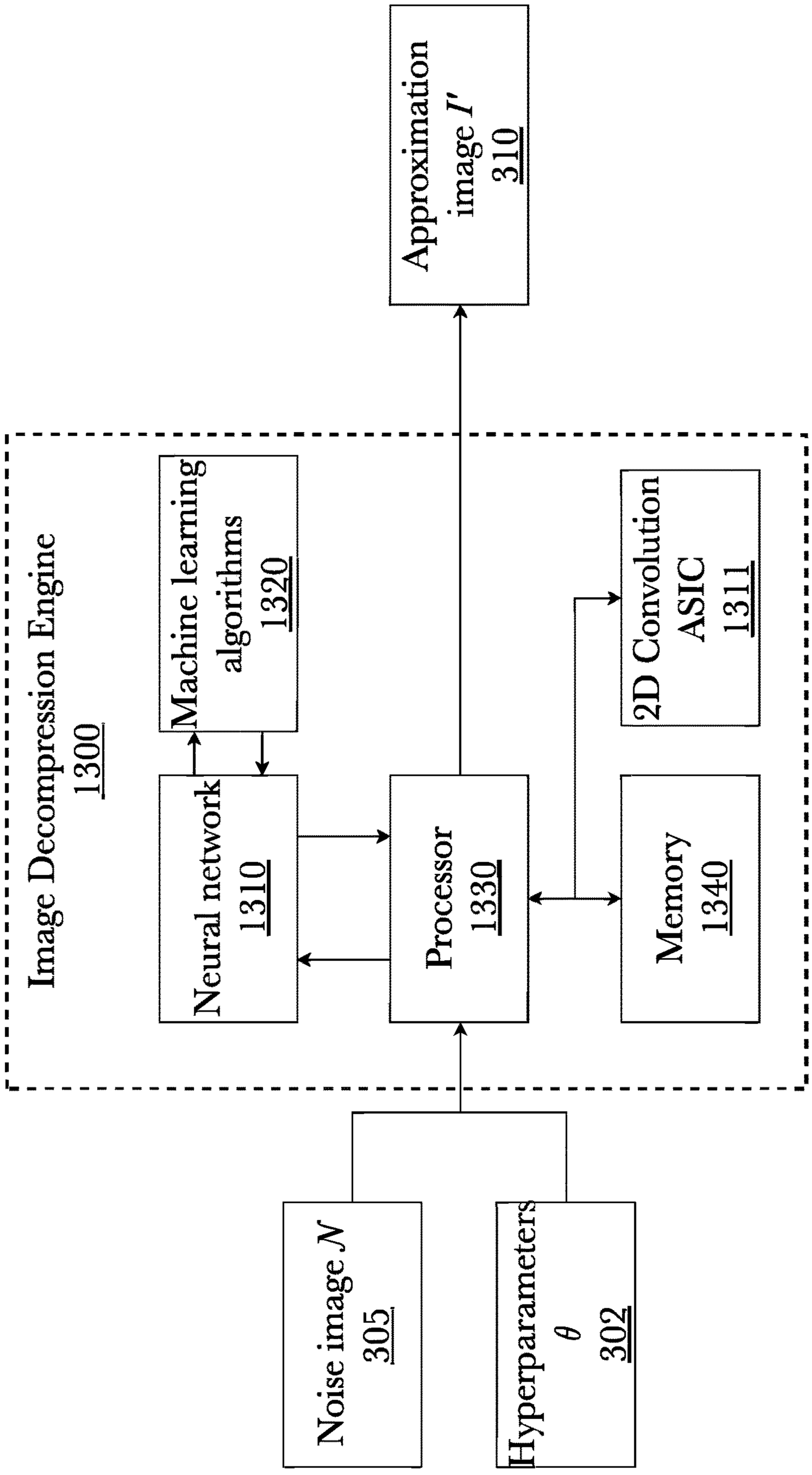

Approximation image I′ 310
Image Decompression Engine 1300
Machine learning algorithms 1320
Neural network 1310
Processor 1330
2D Convolution ASIC 1311
Memory 1340
Noise image N 305
Hyperparameters θ 302

Fig. 13

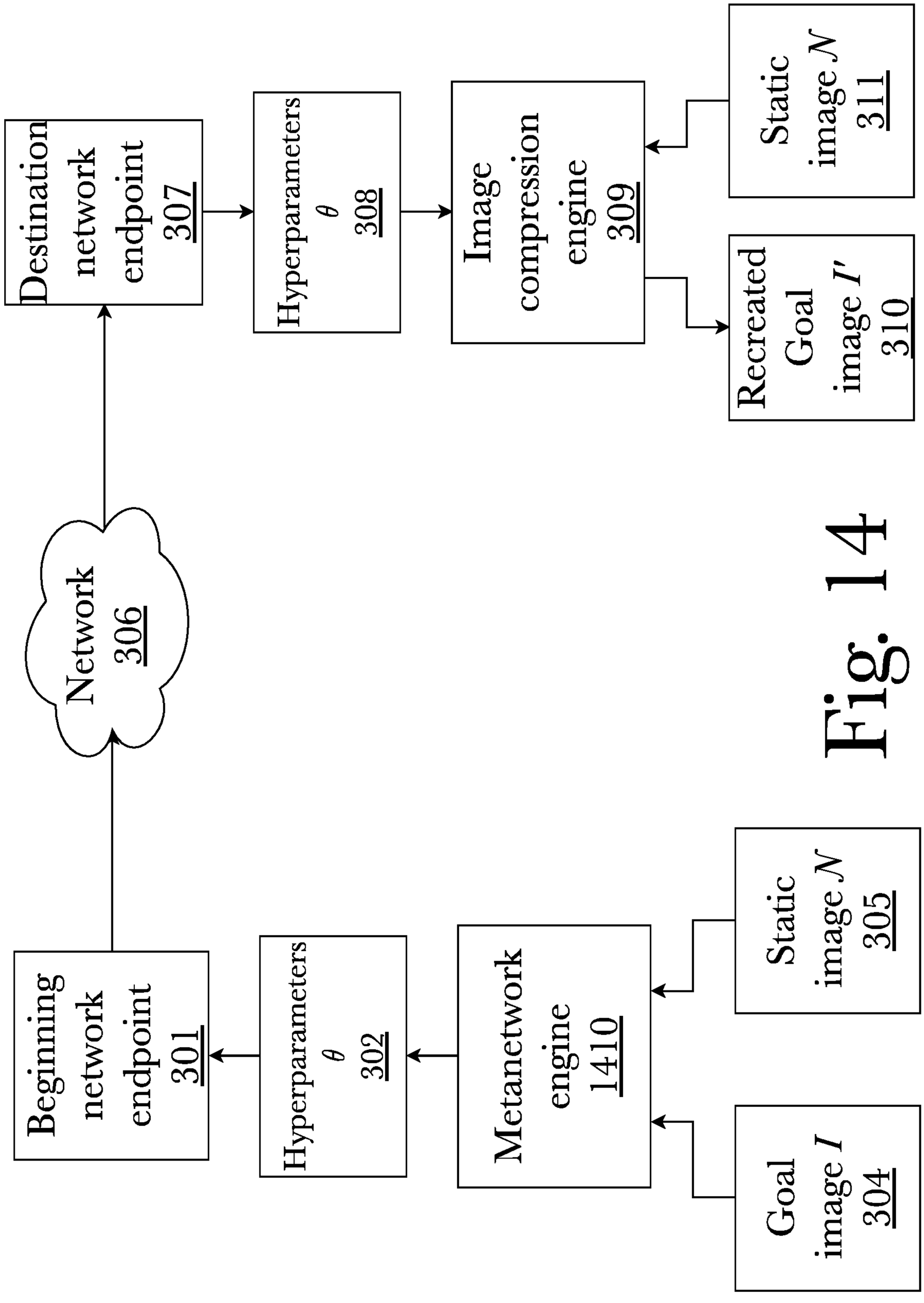

Beginning network endpoint 301
Hyperparameters θ 302
Metanetwork engine 1410
Goal image I 304
Static image N 305
Network 306
Destination network endpoint 307
Hyperparameters θ 308
Image compression engine 309
Recreated Goal image I′ 310
Static image N 311

Fig. 14

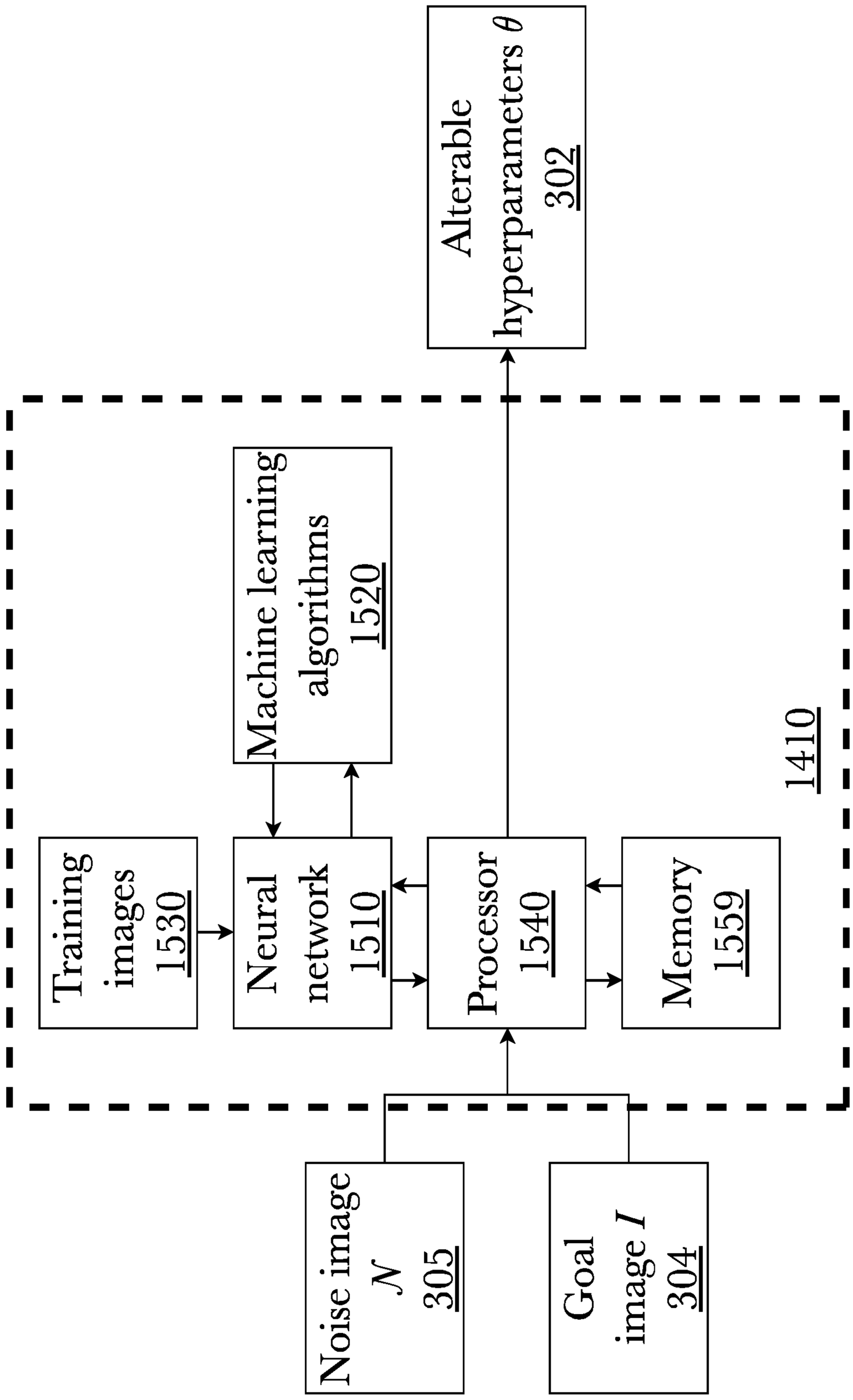
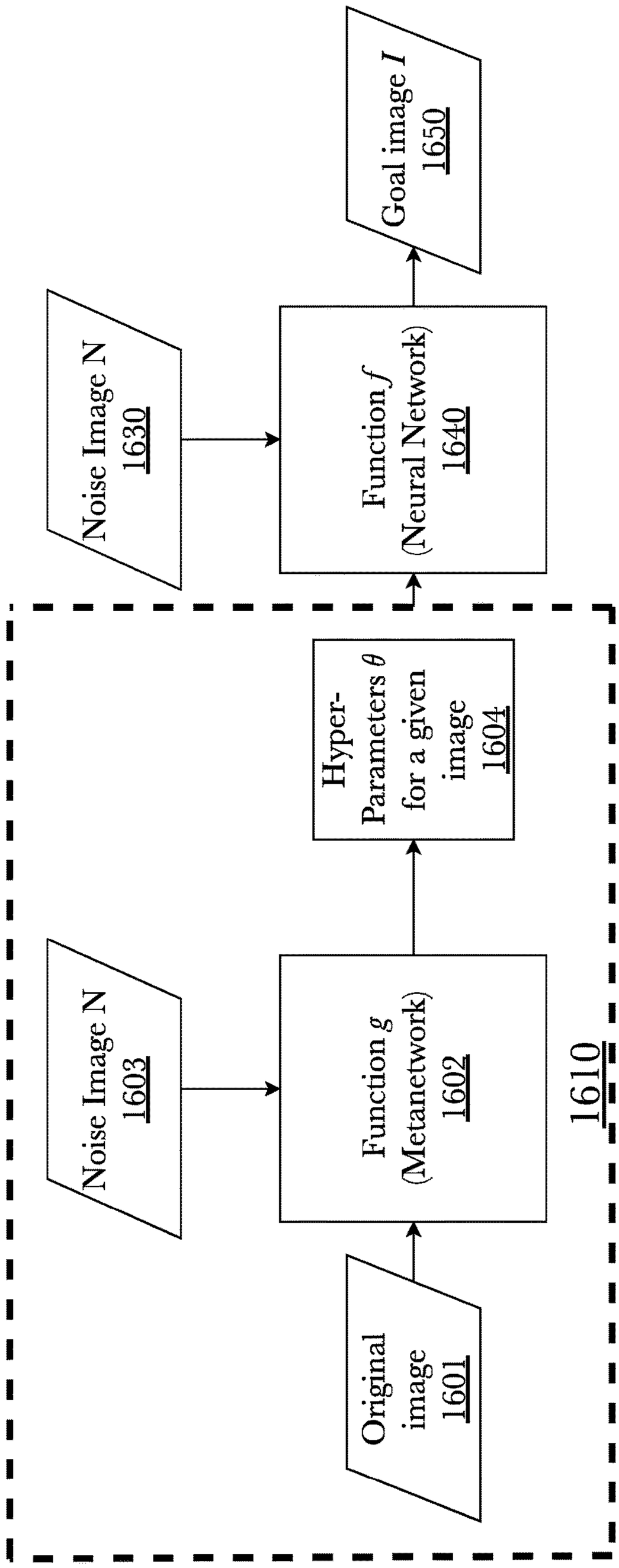

Alterable hyperparameters θ 302
1410
Machine learning algorithms 1520
Training images 1530
Neural network 1510
Processor 1540
Memory 1559
Noise image N 305
Goal image I 304

Fig. 15



Given: $\{I_1,\ldots,I_K\}$, N, $\mathcal{E}$, f

Find: g

So that for $j=\{1,\ldots,K\}$: $g(I_j, N) := \theta'_j$

$f(g(I_j, N)\,|N) := I'_j$

$h(I'_j, I_j) \le \mathcal{E} \Leftrightarrow h(f(g(I_j, N)\,|N), I_j) \le \mathcal{E}$

1620

Fig. 16

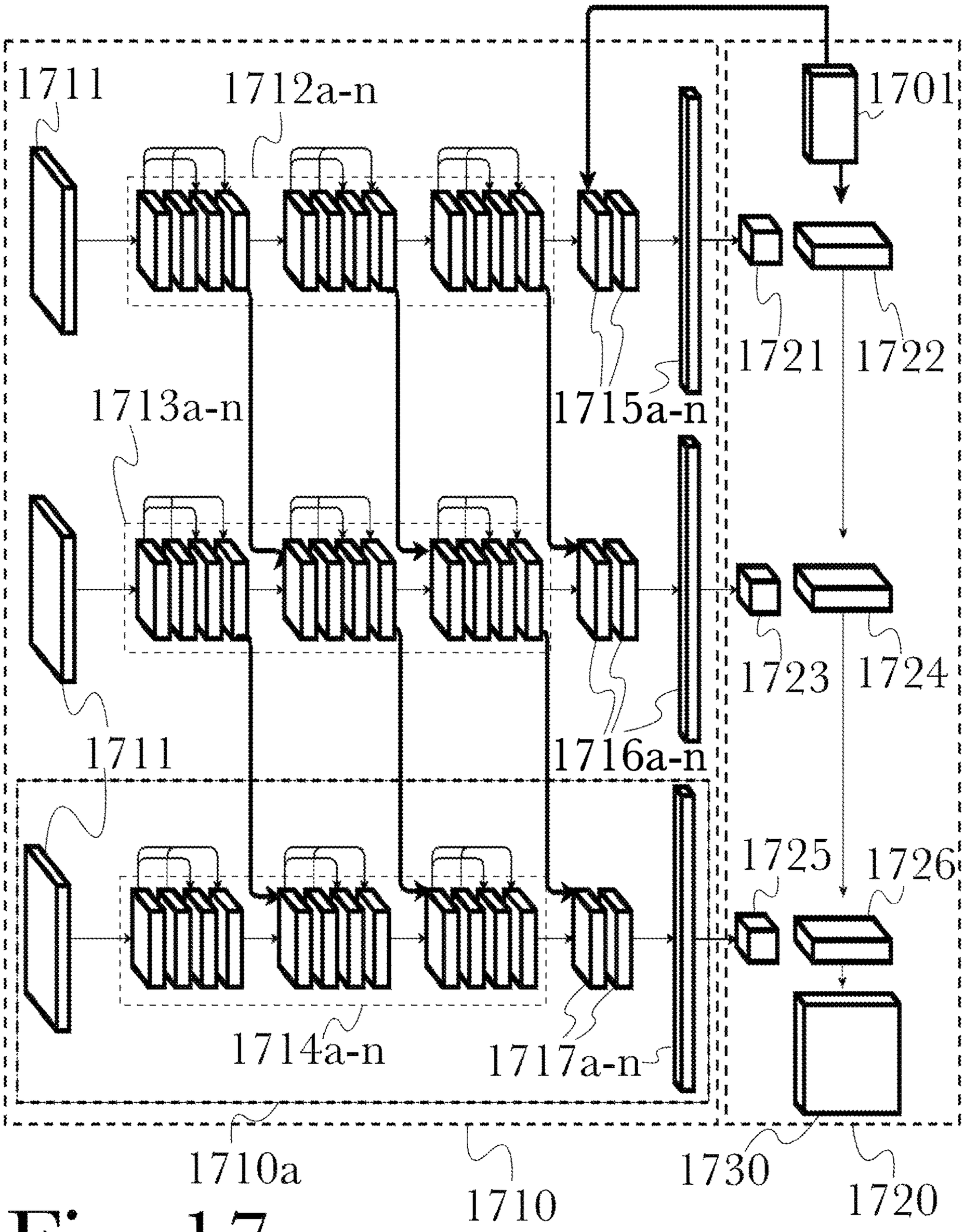

1711
1712a-n
1701
1713a-n
1715a-n
1721
1722
1723
1724
1711
1716a-n
1725
1726
1714a-n
1717a-n
1710a
1710
1730
1720

Fig. 17

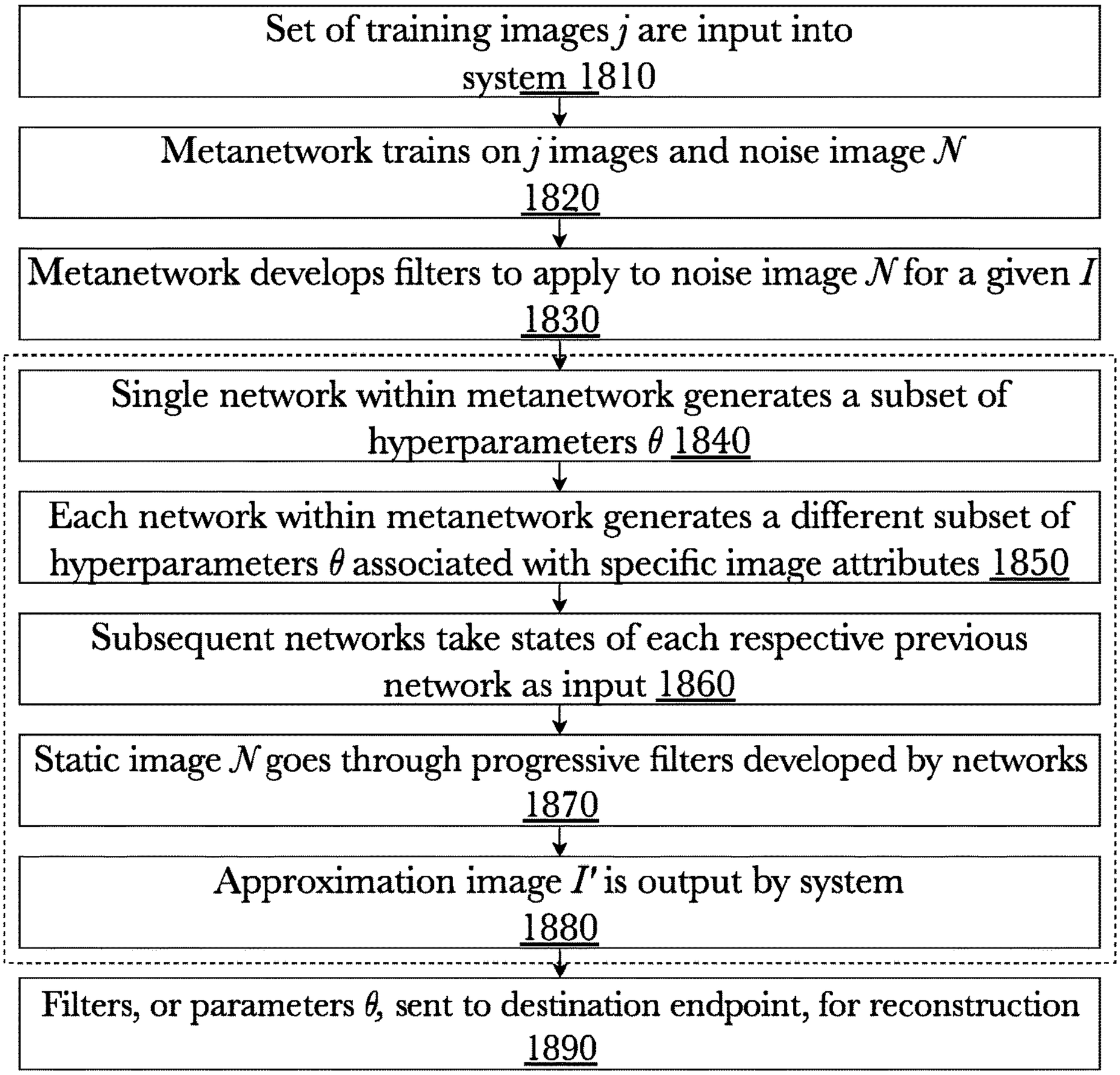

Set of training images j are input into system 1810
Metanetwork trains on j images and noise image N 1820
Metanetwork develops filters to apply to noise image N for a given I 1830
Single network within metanetwork generates a subset of hyperparameters θ 1840
Each network within metanetwork generates a different subset of hyperparameters θ associated with specific image attributes 1850
Subsequent networks take states of each respective previous network as input 1860
Static image N goes through progressive filters developed by networks 1870
Approximation image I' is output by system 1880
Filters, or parameters θ, sent to destination endpoint, for reconstruction 1890

Fig. 18

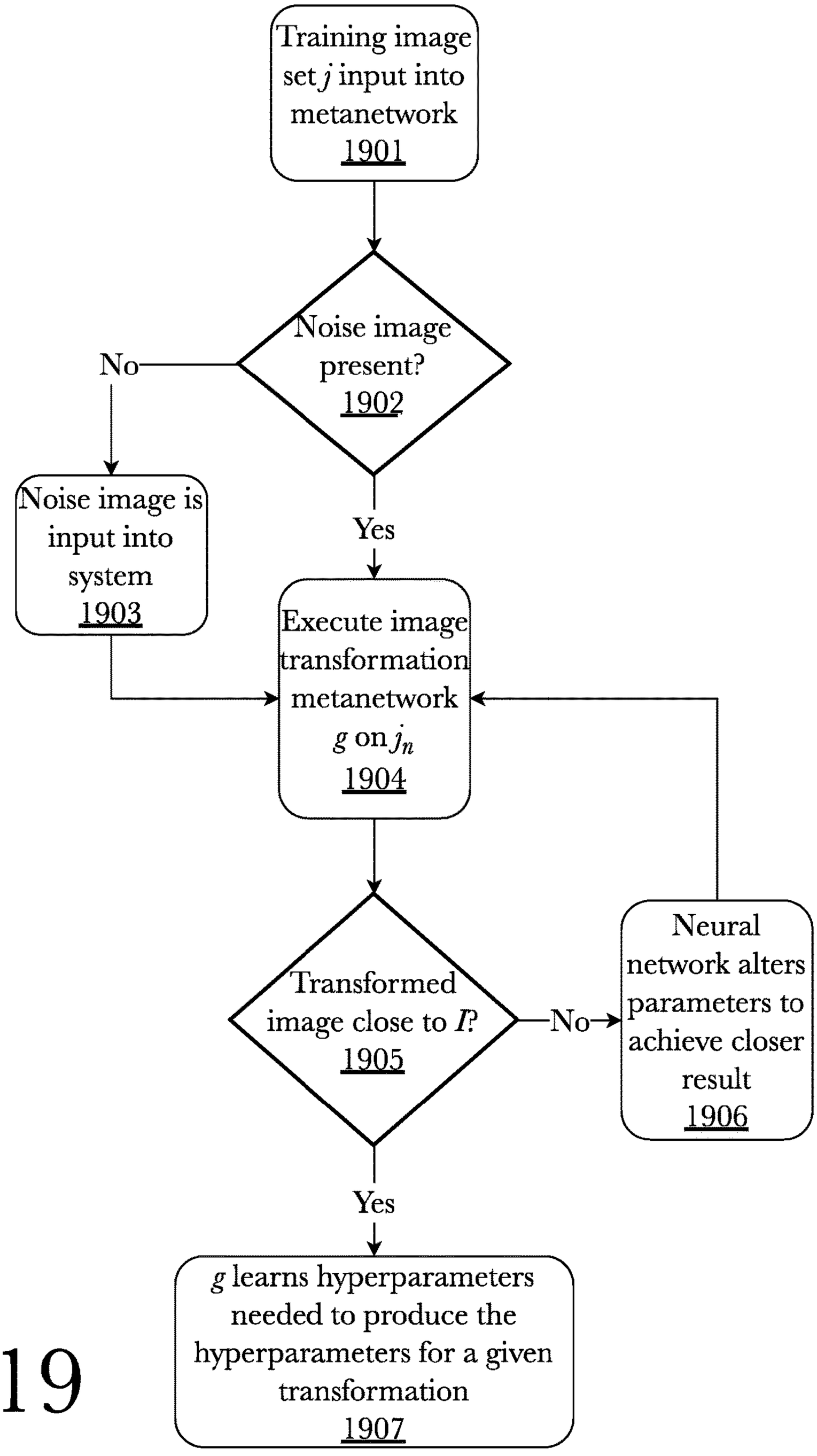

Training image set j input into metanetwork
1901
Noise image present?
1902
No
Noise image is input into system
1903
Yes
Execute image transformation metanetwork g on j_n
1904
Transformed image close to I?
1905
No
Neural network alters parameters to achieve closer result
1906
Yes
g learns hyperparameters needed to produce the hyperparameters for a given transformation
1907

Fig. 19

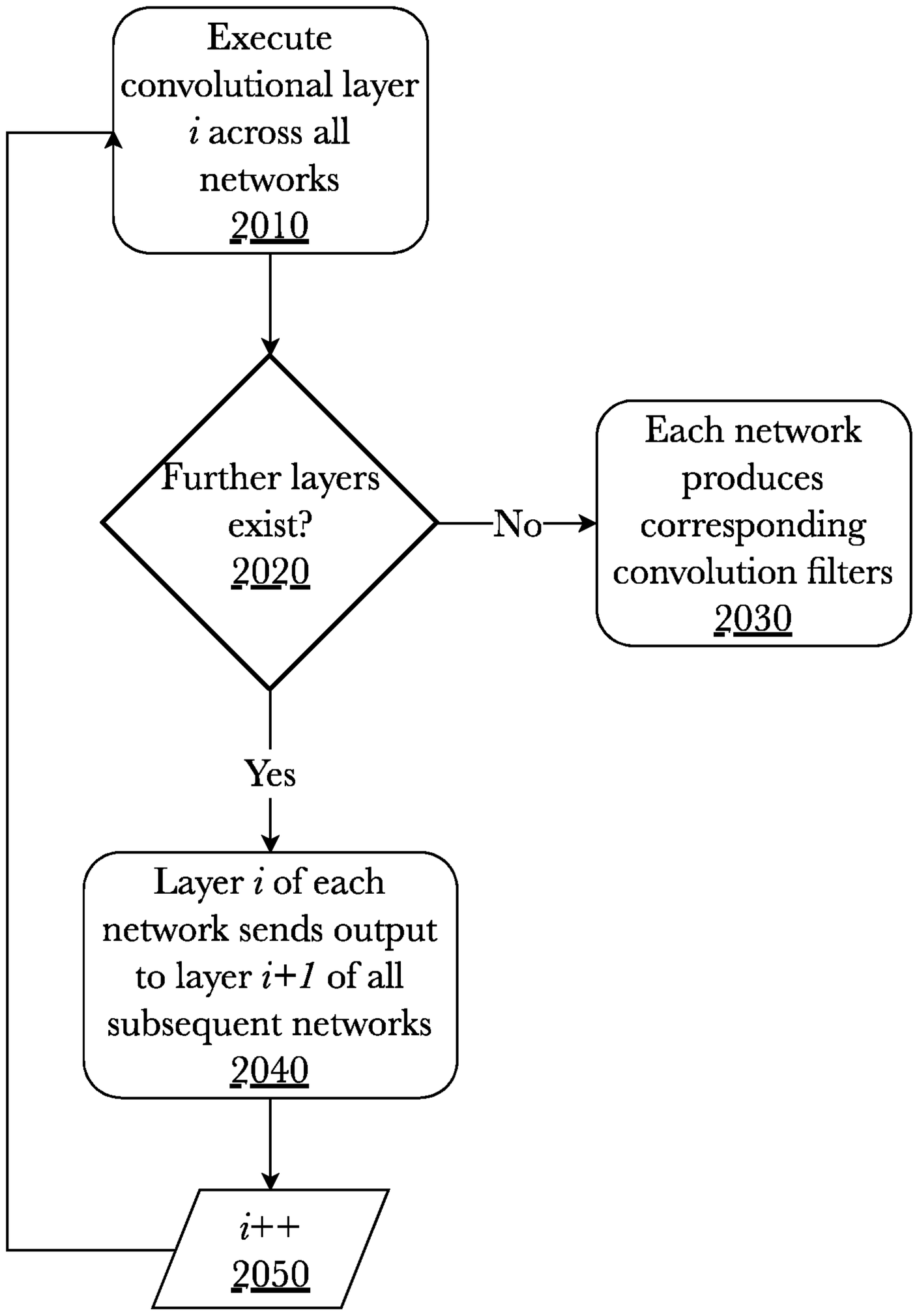

Execute convolutional layer *i* across all networks
2010
Further layers exist?
2020
No
Each network produces corresponding convolution filters
2030
Yes
Layer *i* of each network sends output to layer *i+1* of all subsequent networks
2040
i++
2050

Fig. 20

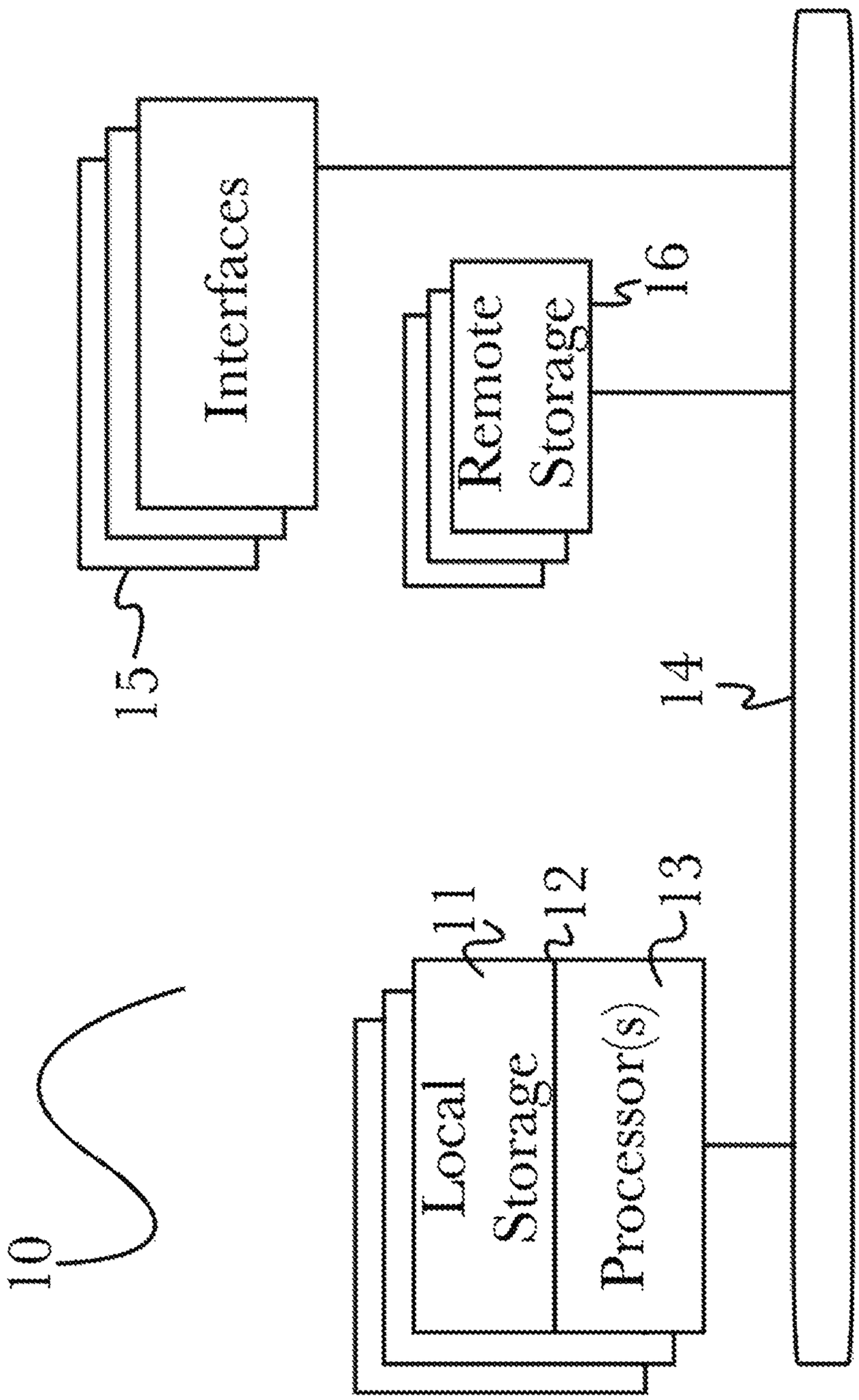

10
Local Storage
Processor(s)
11
12
13
14
Remote Storage
16
Interfaces
15

Fig. 21

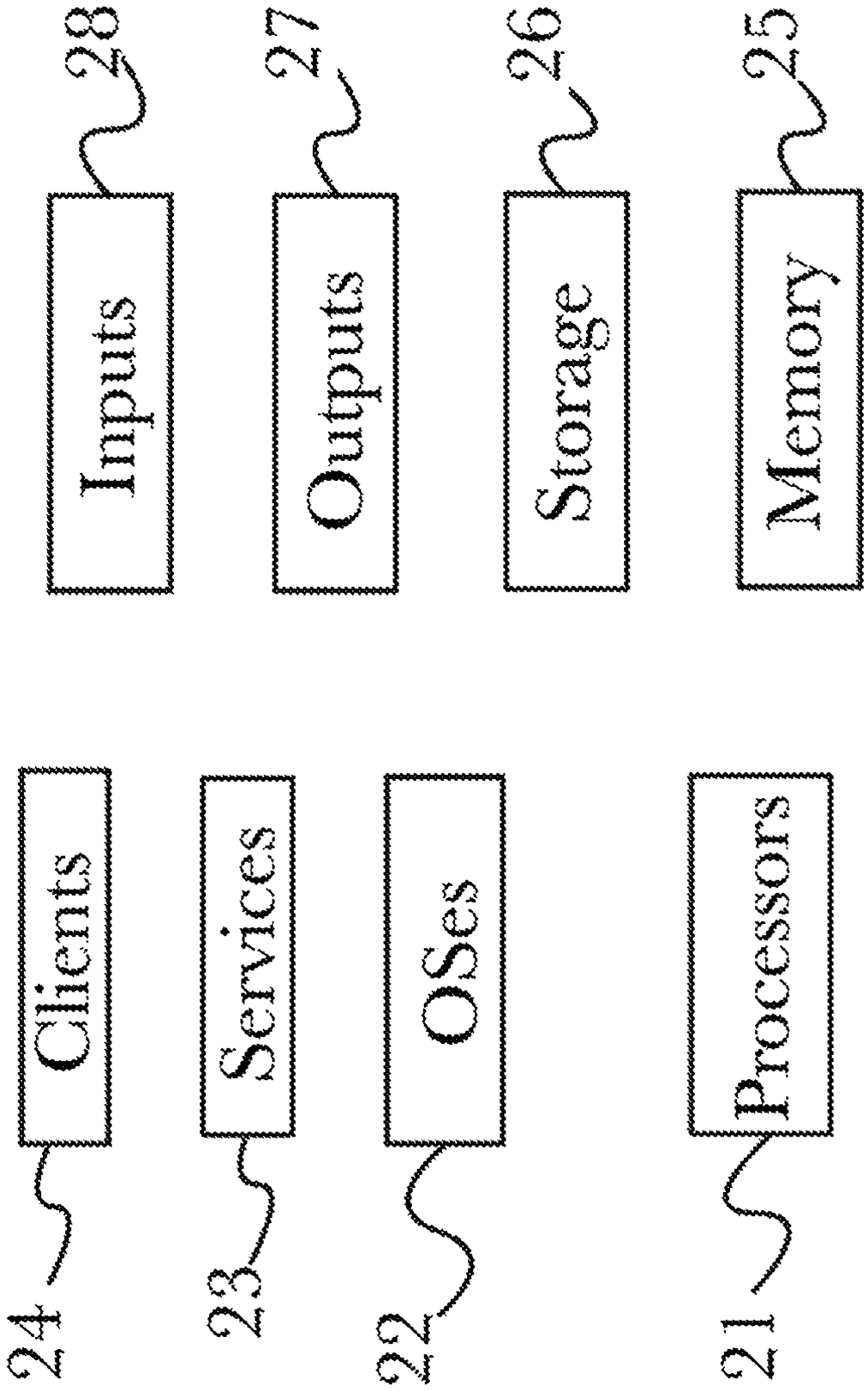

Clients
24
Services
23
OSes
22
Processors
21
Memory
Storage
Outputs
Inputs
20

Fig. 22

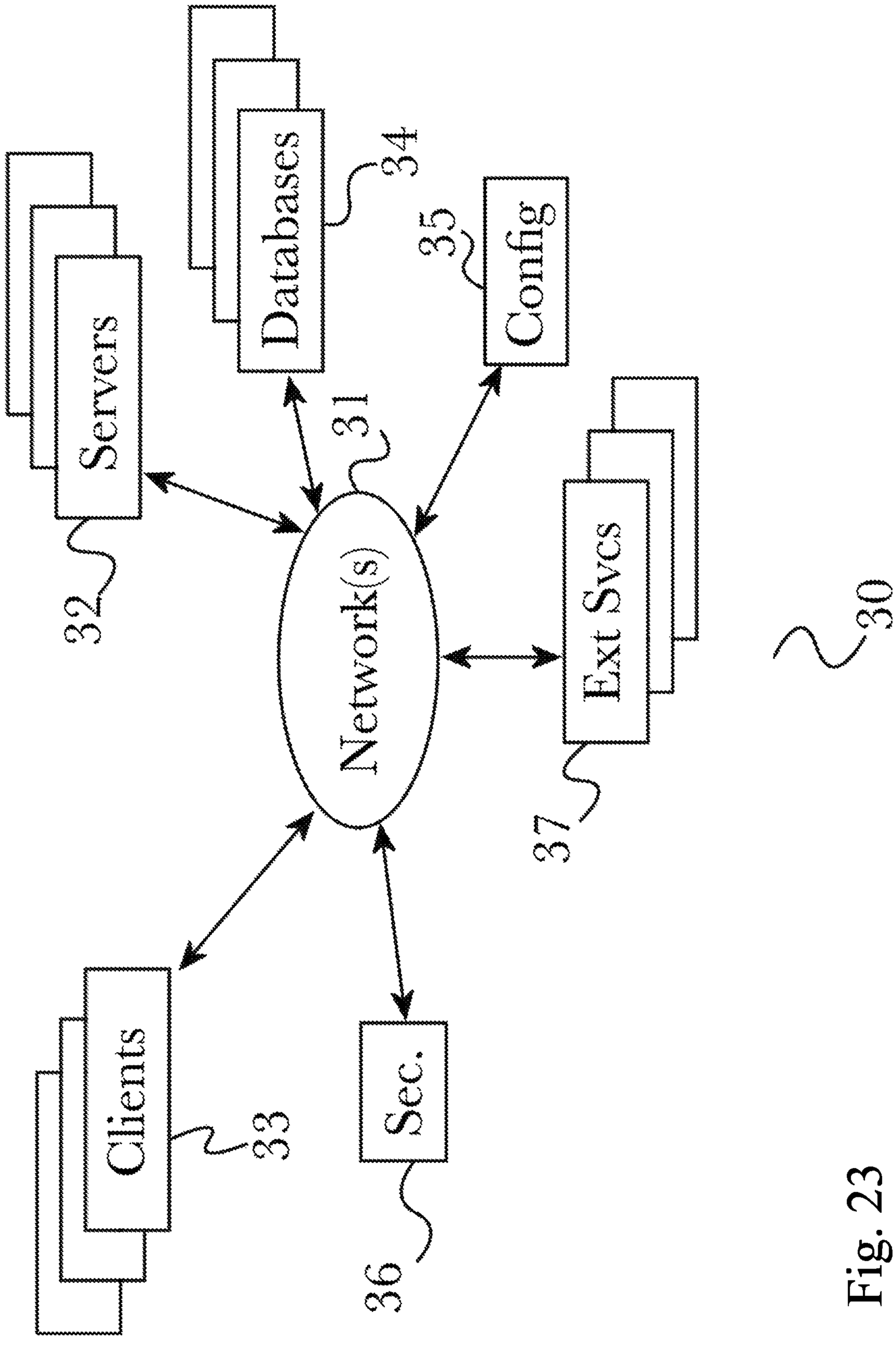

Servers
32
Databases
34
Config
35
31
Network(s)
Ext Svcs
37
30
Clients
33
Sec.
36

Fig. 23

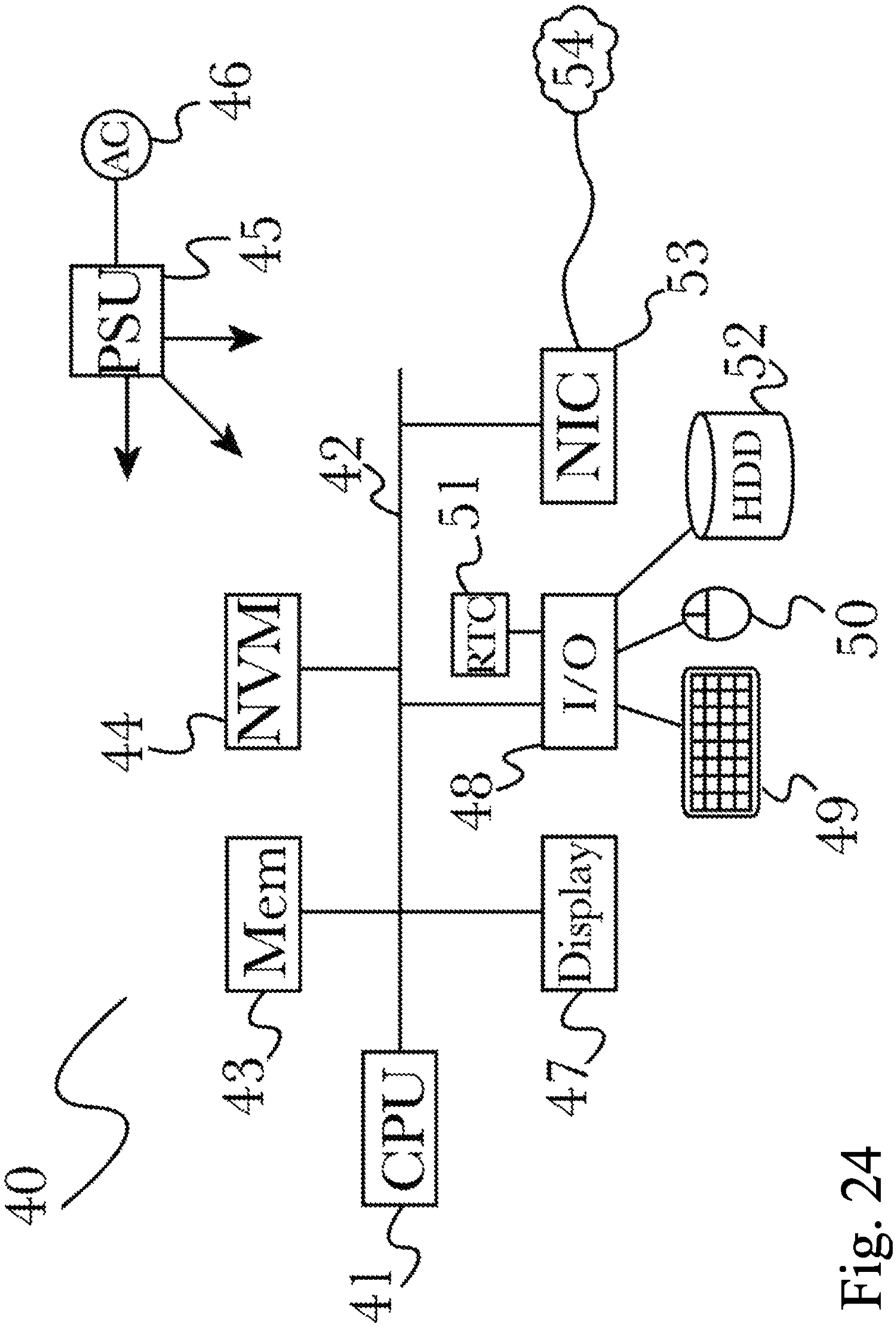

40
41
CPU
42
43
Mem
44
NVM
45
PSU
46
47
Display
48
I/O
49
50
RTC
51
HDD
52
NIC
53
54

Fig. 24

SYSTEM AND METHOD FOR LOSSY IMAGE AND VIDEO COMPRESSION UTILIZING A METANETWORK

CROSS-REFERENCE TO RELATED APPLICATIONS

CROSS-REFERENCE TO RELATED APPLICATIONS		
Application Ser. No.	Date Filed	Title
Current application	Herewith	A SYSTEM AND METHOD FOR LOSSY IMAGE AND VIDEO COMPRESSION UTILIZING A METANETWORK
16/397,725	Apr. 29, 2019	Is a continuation-in-part of A SYSTEM AND METHOD FOR LOSSY IMAGE AND VIDEO COMPRESSION AND TRANSMISSION UTILIZING NEURAL NETWORKS

the entire specification of each of which is incorporated herein by reference.

BACKGROUND OF THE INVENTION

Field of the Art

The disclosure relates to the field of data compression, more specifically to the field of lossy image compression utilizing non-generic neural networks.

Discussion of the State of the Art

Since the start of widespread use of the internet a bit more than two decades ago, there has been an exponential growth in the amount of data being transmitted worldwide. In the past decade, even as the amount of data transmitted continues to grow exponentially, video content has accounted for an ever-increasing portion of those data. According to at least one study, video content accounted for 64% of the world's internet traffic in 2014, and is on track to account for up to 85% of the world's internet traffic in 2019.

Given that the amount of data being transmitted continues to grow exponentially, and that most of the world's internet traffic is now video content, video compression technology has become critically important. However, existing video compression technology has not kept pace with the change. The current leading video compression technologies, High Efficiency Video Coding (HVEC, also known as H.265) and its open-source competitor, AVI are incremental improvements of video compression technologies developed in the early part of this century (i.e., H.264/MPEG-4 AVC and Google's open-source VP coding format). Although the newer video compression standards have improved throughput at the same level of quality versus their older counterparts, that method of video compression may already have hit a point of diminishing returns, and is unlikely to yield significant further improvements.

A method for utilizing a non-generic neural network provides for a significantly reduced amount of data to be transferred for image compression or video frame compression, however such a method, described herein, takes a large amount of time to optimize for finding an optimal network configuration to compress a single image. Therefore, a meta-network which is capable of operating and training on a large data-set, possibly on a powerful platform such as connected computational devices in a datacenter to further

improve efficiency, may be able to be trained to quickly find the structure of a neural network which may re-construct an approximation of an image, thereby allowing many corporations or agencies that require the transfer of large amounts of video or images over a network to accomplish this while utilizing a fraction of the bandwidth currently required even with current compression methods.

What is needed is a system and method for image and video compression whose performance dramatically exceeds the performance of current state of the art image and video compression, without taking a large amount of time to compress the image or video.

SUMMARY OF THE INVENTION

Accordingly, the inventor has conceived and reduced to practice, a system and methods for lossy image and video compression that utilizes a metanetwork to generate a set of hyperparameters necessary for an image encoding network to reconstruct the desired image from a given noise image.

According to a preferred embodiment, a system for lossy image and video compression utilizing a metanetwork, comprising: a metanetwork engine comprising a processor, a memory, and a first plurality of programming instructions stored in the memory, wherein the first plurality of programming instructions, when operating on the processor, cause the processor to: receive a desired image; receive a noise image; receive a set of training images; using the set of training images, train a plurality of neural networks to reconstruct each of the set of training images by mapping the noise image to each of the set of training images; store the parameters for each of the plurality of neural networks as a set of metanetwork hyperparameters; use the set of metanetwork hyperparameters as operating parameters for each of the plurality of neural networks; use the plurality of neural networks to map the noise image to the desired image, producing a second set of hyperparameters corresponding to the specific filters produced from the operation of each of the plurality of neural networks, such that the second set of hyperparameters, when applied to the noise image using the neural network, produce an approximation of the desired image within an error that is less than a pre-determined threshold; and store the second set of hyperparameters for use in future image mapping operations.

According to another preferred embodiment, a method for lossy image compression utilizing a metanetwork, comprising the steps of: receiving a desired image; receiving a noise image; receiving a set of training images; using the set of training images to train a plurality of neural networks to reconstruct each of the set of training images by mapping the noise image to each of the set of training images; storing the parameters for each of the plurality of neural networks as a set of metanetwork hyperparameters; using the set of metanetwork hyperparameters as operating parameters for each of the plurality of neural networks; using the plurality of neural networks to map the noise image to the desired image, producing a second set of hyperparameters corresponding to the specific filters produced from the operation of each of the plurality of neural networks, such that the second set of hyperparameters, when applied to the noise image using the neural network, produce an approximation of the desired image within an error that is less than a pre-determined threshold; and storing the second set of hyperparameters for use in future image mapping operations.

BRIEF DESCRIPTION OF THE DRAWING FIGURES

The accompanying drawings illustrate several aspects and, together with the description, serve to explain the principles of the invention according to the aspects. It will be appreciated by one skilled in the art that the particular arrangements illustrated in the drawings are merely exemplary, and are not to be considered as limiting of the scope of the invention or the claims herein in any way.

FIG. **1** (PRIOR ART) is a method diagram illustrating the HVEC video compression and the similar BPG image compression methodology.

FIG. **2** is a diagram illustrating a flow of objects from compression to decompression stages, illustrating the function used for the disclosed invention, according to an embodiment.

FIG. **3** is a system diagram of high-level components used in the operation of a system for lossy image compression utilizing non-generic neural networks, according to a preferred embodiment.

FIG. **4** is a system diagram of an image compression engine, according to an aspect.

FIG. **5** is a system diagram of an image compression engine as it is utilized for image compression, utilizing a 2D convolution Application Specific Integrated Circuit ("ASIC), according to a preferred aspect.

FIG. **6** is a flowchart illustrating the processing and compression of data through the system, according to an aspect.

FIG. **7** is a flowchart illustrating the processing and decompression of data through the system, according to an aspect.

FIG. **8** is a method diagram of high-level components used in the operation of a system for lossy image compression utilizing non-generic neural networks, according to a preferred embodiment.

FIG. **9** is a state diagram of two users, one encoding and one decoding an image, using the disclosed compression system, according to a preferred aspect.

FIG. **10** is a method diagram illustrating training a neural network with a single image, as opposed to a plurality of images to learn from, resulting in a non-general approach to image compression, according to a preferred embodiment.

FIG. **11** is a diagram illustrating a line-drawn image, and a static image, going into an image compression engine, parameters being identified which allow for a static image to be approximately translated to an initial non-static image, and relayed to a second system over a network to re-generate an approximation of the original image from a static image.

FIG. **12** is a system diagram of an image compression engine used for decompressing an image, according to a preferred aspect.

FIG. **13** is a system diagram of an image compression engine utilizing a specialized 2D convolution Application Specific Integrated Circuit ("ASIC").

FIG. **14** is a system diagram of high-level components used in the operation of a system using a metanetwork to achieve image or video compression, and decompression, according to a preferred embodiment.

FIG. **15** is a system diagram of a metanetwork engine, used to train a metanetwork with a set of training images, and used to compress and find filters that may be used to transform a noise image into an approximation of an input image, according to a preferred embodiment.

FIG. **16** is a dataflow diagram of a system for lossy compression utilizing a metanetwork to train, compress, and send data for decompression to a system utilizing a specific neural network configuration, according to an embodiment.

FIG. **17** is a system diagram of multiple individual networks communicating with each other within a metanetwork, to produce a sequence of convolutional filters to be applied to a noise image, to progressively transform the image into an approximation of an input image, according to an embodiment.

FIG. **18** is a method diagram illustrating steps required for lossy compression of images and video using a metanetwork.

FIG. **19** is a flowchart of the steps taken for a single network within a metanetwork to train on a set of images and produce a network operating as a portion of function g, for neural network hyperparameter prediction of an image encoding network f, according to an embodiment.

FIG. **20** is a flowchart of the process of multiple networks communicating within a metanetwork for the purposes of cross-training and developing progressive filters to transform a static image with, to help alleviate the vanishing gradient problem, according to an embodiment.

FIG. **21** is a block diagram illustrating an exemplary hardware architecture of a computing device.

FIG. **22** is a block diagram illustrating an exemplary logical architecture for a client device.

FIG. **23** is a block diagram showing an exemplary architectural arrangement of clients, servers, and external services.

FIG. **24** is another block diagram illustrating an exemplary hardware architecture of a computing device.

DETAILED DESCRIPTION

The inventor has conceived, and reduced to practice, a system and methods for lossy image and video compression that utilizes a metanetwork.

One or more different aspects may be described in the present application. Further, for one or more of the aspects described herein, numerous alternative arrangements may be described; it should be appreciated that these are presented for illustrative purposes only and are not limiting of the aspects contained herein or the claims presented herein in any way. One or more of the arrangements may be widely applicable to numerous aspects, as may be readily apparent from the disclosure. In general, arrangements are described in sufficient detail to enable those skilled in the art to practice one or more of the aspects, and it should be appreciated that other arrangements may be utilized and that structural, logical, software, electrical and other changes may be made without departing from the scope of the particular aspects. Particular features of one or more of the aspects described herein may be described with reference to one or more particular aspects or figures that form a part of the present disclosure, and in which are shown, by way of illustration, specific arrangements of one or more of the aspects. It should be appreciated, however, that such features are not limited to usage in the one or more particular aspects or figures with reference to which they are described. The present disclosure is neither a literal description of all arrangements of one or more of the aspects nor a listing of features of one or more of the aspects that must be present in all arrangements.

Headings of sections provided in this patent application and the title of this patent application are for convenience only, and are not to be taken as limiting the disclosure in any way.

Devices that are in communication with each other need not be in continuous communication with each other, unless expressly specified otherwise. In addition, devices that are in communication with each other may communicate directly or indirectly through one or more communication means or intermediaries, logical or physical.

A description of an aspect with several components in communication with each other does not imply that all such components are required. To the contrary, a variety of optional components may be described to illustrate a wide variety of possible aspects and in order to more fully illustrate one or more aspects. Similarly, although process steps, method steps, algorithms or the like may be described in a sequential order, such processes, methods and algorithms may generally be configured to work in alternate orders, unless specifically stated to the contrary. In other words, any sequence or order of steps that may be described in this patent application does not, in and of itself, indicate a requirement that the steps be performed in that order. The steps of described processes may be performed in any order practical. Further, some steps may be performed simultaneously despite being described or implied as occurring non-simultaneously (e.g., because one step is described after the other step). Moreover, the illustration of a process by its depiction in a drawing does not imply that the illustrated process is exclusive of other variations and modifications thereto, does not imply that the illustrated process or any of its steps are necessary to one or more of the aspects, and does not imply that the illustrated process is preferred. Also, steps are generally described once per aspect, but this does not mean they must occur once, or that they may only occur once each time a process, method, or algorithm is carried out or executed. Some steps may be omitted in some aspects or some occurrences, or some steps may be executed more than once in a given aspect or occurrence.

When a single device or article is described herein, it will be readily apparent that more than one device or article may be used in place of a single device or article. Similarly, where more than one device or article is described herein, it will be readily apparent that a single device or article may be used in place of the more than one device or article.

The functionality or the features of a device may be alternatively embodied by one or more other devices that are not explicitly described as having such functionality or features. Thus, other aspects need not include the device itself.

Techniques and mechanisms described or referenced herein will sometimes be described in singular form for clarity. However, it should be appreciated that particular aspects may include multiple iterations of a technique or multiple instantiations of a mechanism unless noted otherwise. Process descriptions or blocks in figures should be understood as representing modules, segments, or portions of code which include one or more executable instructions for implementing specific logical functions or steps in the process. Alternate implementations are included within the scope of various aspects in which, for example, functions may be executed out of order from that shown or discussed, including substantially concurrently or in reverse order, depending on the functionality involved, as would be understood by those having ordinary skill in the art.

Definitions

"Artificial intelligence" or "AI" as used herein means a computer system or component that has been programmed in such a way that it mimics some aspect or aspects of cognitive functions that humans associate with human intelligence, such as learning, problem solving, and decision-making. Examples of current AI technologies include understanding human speech, competing successfully in strategic games such as chess and Go, autonomous operation of vehicles, complex simulations, and interpretation of complex data such as images and video.

"Function," "image transformation function," "image transformation network," and "image transformation neural network" as used herein mean the use of a neural network as a function to transform an image or to re-create an approximation of an image. The transformation is based on mapping of a noise image to a target image, and adjustment of the weights of differing variables within the function, which may also be referred to as hyperparameters. Hyperparameters may also be used an inputs to the function, along with the noise image, to re-create an approximation of the image.

"Hyperparameter" as used herein means the parameters of a function that maps a noise image to a target image within a specified margin of error. When an image is input into the function for mapping at a source location, hyperparameters will be the output. The hyperparameters may then be transferred to a destination location, wherein the hyperparameters will be the input to the same (or similar) function with the same noise image, and the output of the function will be an approximation of the desired image at the destination location.

"Goal image", also referred to interchangeably as a "target image" or "desired image" as used herein means a digital representation of an image. This digital representation may be in any image file format, of which there already exist a great number. Image files are commonly classified as either raster-based formats (i.e., formats in which the content of pixels or areas of the image are specified) or vector-based (i.e., formats in which shapes and their relationships are specified without regard to specific pixels, areas, or image sizes). For exemplary purposes, a non-exhaustive and non-limiting list of raster-based formats includes Microsoft Windows bitmap (bmp), CompuServe Graphics Interchange Format (gif), Joint Photographic Experts Group JFIF format (jpg or jpeg), Portable Graphics Network (png), and Tagged Image File Format (tif or tiff). For exemplary purposes, a non-exhaustive and non-limiting list of vector-based formats includes Adobe Illustrator File (ai), CorelDRAW Image File (cdr), Scalable Vector Graphics File (svg), and Microsoft Visio Drawing File (vsd).

"Image transformation" as used herein means the act of transforming any image, or even a blank or "empty" image file, into any other image. This may be done with numerous different techniques, in any combination, including specific pixel alterations, the use of vector graphics based on mathematical equations (for example, graphing curves with equations which yield perfect resolution no matter the zoom on the image itself, since it is specified with an equation rather than represented by specific pixels at a given resolution), or examining and altering groups of pixels such as for border detection and alteration. Altering the positions of pixels of data in an image, but keeping the data otherwise unchanged, for example rotating an image, is another example of an image transformation.

"Machine learning" as used herein is an aspect of artificial intelligence in which the computer system or component can modify its behavior or understanding without being explicitly programmed to do so. Machine learning algorithms develop models of behavior or understanding based on information fed to them as training sets, and can modify those models based on new incoming information. An

example of a machine learning algorithm is AlphaGo, the first computer program to defeat a human world champion in the game of Go. AlphaGo was not explicitly programmed to play Go. It was fed millions of games of Go, and developed its own model of the game and strategies of play.

"Neural network" as used herein means a computational model, architecture, or system made up of a number of simple, highly interconnected processing elements which process information by their dynamic state response to external inputs, and is thus able to "learn" information by recognizing patterns or trends. Neural networks, also sometimes known as "artificial neural networks" are based on our understanding of the structure and functions of biological neural networks, such as the brains of mammals. A neural network is a framework for application of machine learning algorithms.

"Static noise image", also referred to as a "static image" or "noise image" as used herein means an image with random or pseudo-random content. In some embodiments, the random or pseudo-random content will be at the pixel level, or be at the level of groups, areas, or regions of pixels. In some embodiments, the random or pseudo-random content may comprise a single bit per pixel, representing either black or white for that pixel. In some embodiments, the randomness property of the image may be the 2D maximum information entropy, or Shannon Entropy, as part of its properties. Shannon Entropy refers to the amount of randomness or possible information a given statistical model can have, expressed in bits. For example, a coin flip has an information entropy or Shannon Entropy of 1, while m coin flips have an entropy value of m, because a single coin flip has a value or 0 (tails) or 1 (heads), represented by 1 bit. The higher the entropy value for a given object, the more possible states it may be in, which makes it harder to predict the state of, but more malleable for transforming into many possible states and acquire an estimation of another state, for example, transforming into an approximation of another image. In some embodiments, the random or pseudo-random content may further comprise grayscale or color information. In some embodiments, the random or pseudo-random content may comprise vector graphics or other forms of image representation instead of bitmaps or pixels.

"Video" as used herein means a digital representation of a sequence of images representing movement. This digital representation may be in any video file format, of which there already exist a great number. Video files typically contain coded video (visual) data and audio (audible) data in a "container." This application is primarily concerned with the video data portion of a video file. For exemplary purposes, a non-exhaustive and non-limiting list of video formats includes Audio Video Interleave (avi), Motion Pictures Expert Group (mpg, mpeg, mp2, mp4, etc.), Apple video format (m4v), and Windows Media Video (wmv).

Conceptual Architecture

FIG. **1** (PRIOR ART) is a method diagram illustrating the HEVC video compression and the similar BPG image compression methodology. First, an image or video file is input into a compression codec or compression engine **110**, before data files are encoded with intra-frame chunks **120** which remain unchanging through frames of a video in the case of HEVC video file compression, meaning that between frames of a video where a grouping of pixels do not change or change very little, that grouping is not re-encoded in multiple frames of the video **130**, thereby reducing the size of the video with only a minor loss of movement in frames. In the case of BPG formatting for still images rather than video for HEVC video formatting, clusters of similar data including color depth are maintained for groups of pixels in a still image **130**, representing a decrease in the data required for equivalently sized images, resulting in a compressed format using similar techniques for both video and still images **140**.

FIG. **2** is a diagram illustrating an exemplary algorithm for implementation of an aspect of a preferred embodiment. In this algorithm, a desired image **201** and a noise image **203** are input into a function f **202**. Function f **202** is a neural network configured to map noise image **203** to a desired image **201**. The output of function f **202** is a set of hyperparameters P **204**, or "weights" of function f **202**, that map the noise image **202** to the desired or target image **201** within a specified margin of error. The mathematical formula for this algorithm is:

Given: I, N, find θ, such that:

$$f{:}R^{W_N*H_N*C_N}\rightarrow R^{I_N*I_N*I_N}, \text{ where } f(\theta|N){:=}I' \text{ and } h(I',I)\leq$$

The algorithm may be generally described as follows. Given a color image I (which corresponds to target or desired image **201**), with width W_I, height H_I and depth C_I, there is an algorithm **220** which may find a mapping between a given max-entropy image N of size $W_N \times H_N \times C_N$ and I, by fine-tuning the hyperparameters θ of a known function f **202**. However, such an algorithm is only capable of reconstructing an approximation of the original image, allowing an error up to a defined threshold. The algorithm **220** measures the error between two images through a function h which may be one of several possible image comparison functions, such as a pixel-wise mean-square-error function. If for all images I there exists an f **202** with θ_f such that the above statement holds true, then it is possible to approximately represent all images via a triplet of {f, θ_f, N}. If function f **202** is fixed, and its input N, the only thing missing to create I' is θ. If the file size of θ is smaller than the file size of I, the algorithm has successfully lossy-compressed I, because one only need send θ with a bitstream of size filesize(θ) to create I' from the triplet {f, θ, N} at a destination device, by inputting noise image **206** and parameters θ **204** into f **205** on the destination/receiving side to obtain approximated target image I' **207**.

However, it is not immediately obvious how to choose a function f that will efficiently find θ. The solution is to use a neural network with its typical structure of convolution→bias→non-linearity→repeat as function f. By using a neural network as function f, the solution to finding its hyperparameters θ given I becomes a machine learning training problem that can be solved using, for example, stochastic gradient descent (SGD). In short, SGD is used to learn the hyperparameters (aka weights) which minimize the error function h, thus obtaining θ for I.

After hyperparameters θ **204** are output from a neural network **202**, they may be input into a separate instance of the same or a similar neural network **205**, along with a separate instance of an identical noise image **206**, to produce an approximation of a desired image I **207**. In this way, the system operates as compressor and decompressor, by generating one of two objects depending on what is received as input, either hyperparameters θ **204** or an approximation of an image I **207**. The instances of these objects, such as the decompression neural network **205** and associated data, may be operating on different computers, for example a first network endpoint possessing a desired image I **201**, function f **202**, and noise image **203**, may operate on one computer such as a smartphone, laptop, or other computing device, while another function f **205**, noise image **206**, may exist on another computing device, possibly but not necessarily over

a network. It is possible, for instance, for files to be transferred via a portable memory device, rather than over a network between two computers. It is important to note that the different instances of the neural network at either end of a transmission need not be identical. Neural networks that function similarly will produce an acceptable solution, even if their architecture, programming, or other characteristics are different.

FIG. **3** is an exemplary overall system diagram, according to a preferred embodiment. A network endpoint **301**, which may be a laptop or desktop computer, a mobile phone, a workstation, or some other manner of network-enabled computing device, may be connected over a network **306** such as the Internet, and possess a desired image I **304** and noise image N **305**. On a network endpoint **301**, both images may be used as inputs for an image compression engine **303**, which is directly accessible by a network endpoint **301**. A desired image I **304** may be in one of many image formats, including .JPG/.JPEG, .PNG, .BMP, or other formats, the specific format of it being a non-crucial element to the instant invention, as new formats may be identified and accounted for in the future as applicable. A static noise image N **305** may similarly be in one of many formats, and may be a singular, unchanging image, which is used in all implementations of the system, or it may be one of several possible images, and sent to the system as input from another source, whether a network endpoint **307** or some other source containing the image. In some embodiments, the static noise image N **305** represents an image that has the highest 2D Shannon Entropy, which may be used for transformation into other images as needed. An image compression engine **303** is an engine present on a network endpoint **301**, which may take, as input, a desired image I **304** and static noise image N **305**, and execute an image transformation function **202** to generate hyperparameters for the function **202** which, when applied to the noise image N **350**, allow the recreation of a close approximation I' (read as "I-prime" and denoting an approximation of I) **310** of a desired image I **304**. Specifically, a destination endpoint **307** may receive hyperparameters **308** for input into another instance of an image decompression engine **309**, also using a static noise image **311** as input, allowing it to produce an approximation **310**, I', of a desired image I **304**.

FIG. **4** is an exemplary system diagram of an image compression engine **303**, according to a preferred embodiment. As shown in FIG. **3**, a noise image N **305**, and goal image I **304**, which respectively represent a maximum entropy noise image and the initial image to be compressed, are input into a processor **430**. A processor **430** is a common computing device used to process arithmetic and logical operations, and is commonly known in the art. A processor **430** has two-way communication with at least a single bit of volatile memory **440**, commonly known as Random Access Memory ("RAM"), for short-term storage of data to be accessed by a processor **430**, the processor altering data in the RAM and using data in the RAM to alter its own processes. This is commonly understood as one of the key interactions in modern computing. A processor **430** also communicates with a neural network **410**, which operates as a function f in an algorithm **220**, operating as a framework for machine learning algorithms **420** to process incoming data from a noise image **305** and goal image **304**. After an input image **304** is re-created approximately, using the algorithm **220** in FIG. **2**, the hyperparameters **302** of a neural network **410** are output to the network endpoint **301** for further use, including transmitting to a destination endpoint, saving on a hard-drive or external memory device, or other common uses for compressed images.

FIG. **5** is a system diagram of another exemplary embodiment of an image compression engine **500**, utilizing a 2D convolution Application Specific Integrated Circuit ("ASIC") **560**, according to an embodiment. In this embodiment, a 2D convolution ASIC **560** is utilized to reduce the amount of processing time required for the system to fully compress an image. As shown in FIG. **3**, a noise image N **305**, and goal image I **304**, which respectively represent a maximum entropy noise image and the initial image to be compressed, are input into a processor **530**. A processor **530** is a common computing device used to process arithmetic and logical operations, and is commonly known in the art. A processor **530** has two-way communication with at least a single bit of volatile memory **540**, commonly known as Random Access Memory ("RAM"), for short-term storage of data to be accessed by a processor **530**, the processor altering data in the RAM and using data in the RAM to alter its own processes. This is commonly understood as one of the key interactions in modern computing. A 2D convolution ASIC **511** also communicates bi-directionally with both the system processor **530** and memory **540**, in order to handle specialized processing of convolutional neural network **510** data much faster than a general central processing unit might otherwise achieve. A processor **530** also communicates with a neural network **510**, which operates as a function f in an algorithm **220**, operating as a framework for machine learning algorithms **520** to process incoming data from a noise image **305** and goal image **304**. After an input image **304** is re-created approximately, using the algorithm **220** in FIG. **2**, the hyperparameters **302** of a neural network **510** are output to the network endpoint **301** for further use, including transmitting to a destination endpoint, saving on a hard-drive or external memory device, or other common uses for compressed images.

FIG. **6** is a flowchart illustrating the processing and compression of data through the system, according to an aspect. A desired image I may be input into the system **601**, this being the image that the system will attempt to transform a noise image into with specific hyperparameters. A check for a noise image is performed **602**, which may yield either positive or negative results, regarding whether the system already possesses a static noise image **305**. If there is no static noise image currently present in the system, a noise image may be input into the system **603**, through a network endpoint **307** which may possess a static noise image, or it may be generated automatically, or come from some other source. If a static noise image is already present, or after it is received or input into the system **603**, the system is at a state of both the static noise image N **305** and desired image I **304** being present in the system. It is at this point that an image transformation function f may be utilized or executed **604** to apply to a static noise image N **305**, the result of the transformation being checked for closeness to a desired image I **605**. the closeness being defined by an error value, the hyperparameters of the neural network are output **607**, and the system ends execution, ready to receive a new input image and begin execution again **601**. If the image transformation function f **410** operating on a noise image N **305** does not yield a sufficiently close result to desired image I **304**, then a neural network **410** may alter the alterable hyperparameters θ **302** of a transformation neural network f **410**, **606** to attempt to produce ever-closer results, until the output is sufficiently close to an image I **304**, **605**.

FIG. **7** is a flowchart illustrating the processing and de-compression of data through the system, according to an

aspect. First, hyperparameters are received and input into an image compression engine **701**, which apply to the neural network **410** to determine the image transformation and convolution of a noise image into a desired image. The system is checked to ensure that a static noise image N is present **702**, and if no noise image is present, such an image is input into the system **703**, which may be sent from the same source as the alterable hyperparameters θ, or may be inserted by a separate system, or manually input by a user on the system itself. After a noise image N is inserted into the system **703**, or if the noise image is already present, for example if the noise image remains static and identical across all implementations of the disclosed invention, then an image transformation function f may be executed **704**, however instead of having no input hyperparameters as in FIG. **6**, the hyperparameters are already input into the system **701**, and the static noise image **305** is transformed **704** into an image I', which is an approximation of a desired image I **304**, before being output **705**. In this way, image compression is performed by specifying how to re-create an image rather than altering the image data itself, allowing the specifications for re-creating the image to be transmitted rather than the image itself, ensuring excellent compression of data.

FIG. **8** is a method diagram of high-level components used in the operation of a system for lossy image compression utilizing neural networks, according to a preferred embodiment. First, a desired image must either be present, or input **801**, this image being the image that will be attempted to be re-created with an image transformation network **410**, before a static noise image N **305** is accessed **802**. This noise image will be utilized by an image transformation function **410** to attempt to translate it, using alterable hyperparameters, into an approximation of an input desired image I **304**. After a noise image is received or accessed if it is static and unchanging **304**, the image transformation function f **410** is executed **803**, utilizing alterable hyperparameters θ **302** and feeding into a set of machine learning algorithms **250** operating on a neural network **260**, resulting in alterable hyperparameters θ for image transformation function f being altered **804**, **805** in an attempt to translate a closer approximation to input image I **304**. When an image is produced from a transformation of a noise image N **305**, the alterable hyperparameters θ **302** are output **806**, such that a user with the image transformation function **410**, noise image **305**, and hyperparameters **302**, may re-create a close approximation of the original desired image **304**. In this way, the image may be heavily compressed, and potentially encrypted from users without access to the image transformation function itself. Alterable hyperparameters θ **302** may then be sent to another network endpoint **307**, **807**, such as another laptop, desktop, or workstation device, or other device capable of running a 2D convolution ASIC as specified in FIG. **5**. A destination network endpoint **307** may then, using alterable hyperparameters θ **302**, execute an image transformation function f **808**, inputting alterable hyperparameters θ **809** as the parameters in which a neural network **410** transforms a noise image **305** to an approximate of a desired image I **304**, **810**.

FIG. **9** is a state diagram of two users, one encoding and one decoding an image, using the disclosed compression system. In a first state **910**, a user A has a desired image I **304**, while a user B wants to receive an image I **304** and does not yet possess it. This is analogous to a user possessing an image to compress and send to another user, perhaps a friend, work colleague, or third-party service which requires for one of many possible reasons that the file be compressed first. In a second state **920**, which necessarily follows from the first, training is undergone with a neural network **410** which allows for the hyperparameters θ **302** to be tuned to allow for an image transformation function to transform a static noise image N **305** into an approximation of a desired image I **304**. A third state **930**, proceeding from the second, allows for user A to acquire the parameters θ **302** as mentioned previously, from the training, before proceeding to a fourth state **940**, in which hyperparameters θ **302** are sent from user A to user B, which allows for a fifth state to be reached **950**, whereby user B, now possessing the hyperparameters θ **302**, may acquire I **304** by utilizing an image transformation function f **410** to transform a noise image N **305** into an approximation of a desired image I **304**.

FIG. **10** is a method diagram illustrating training a neural network with a single image, as opposed to a plurality of images to learn from, resulting in a non-general approach to image compression. A desired image is input into the system **1010**, as has been elaborated on previously in the disclosed system, such an image comprising any two-dimensional graphical file of one of the numerous viable formats including .BMP, .PNG, or others. A neural network **410** is trained **1020** using on a static noise image N **305**, without changing or swapping out the image **305**, resulting in a network trained on a single datapoint rather than a large dataset, unlike generalized neural networks. Rather than feeding a large dataset to a network, edge weights of a network are adjusted based on how close a given output of a network's image transformation has come to a desired image I **304**, **1030**. In this way, training is continued on a network **410** on a single noise image **305**, using adjusted weights and parameters **1040**. A table **1050** illustrates the differences, and relationship, between a traditional neural network which reaches generalized solutions to problems, and the proposed neural network **410**, which utilizes a specialized method of training and does not learn general image transformation techniques, by training on a single noise image iteratively, altering the weights and parameters of the network as it generates new transformed images until a close approximation to the desired image is generated.

FIG. **11** is a diagram illustrating an actual image, and a noise image, going into an image compression engine, parameters being identified which allow for a noise image to be approximately translated to an initial non-noise image, and relayed to a second system over a network to re-generate an approximation of the original image from a noise image. A sample image **1101**, and a static noise image **1102**, are input into an image compression engine **303**. Hyperparameters **303** for re-creating image **1101** are devised through training a neural network to transform a noise image **1102** into a close approximation of a desired image **1101**, the transformation being possible due to the noise image **1102** being a maximally entropic image capable of being transformed into any number of images with the correct transformation steps. Hyperparameters **302** for re-creating an image **1101** are sent over a network **306**, where they are fed into an image decompression engine **309**, along with a copy **1103** of the static noise image **1102**, which outputs a close approximation **1104** of the desired image **1101**. Note that this is not an identical copy, but a close approximation, therefore illustrating a lossy compression method, and creating a separate image file **1104**, not identical to the original image **1101**.

FIG. **12** is a system diagram of an image decompression engine **1200** used for decompressing an image, according to an embodiment. It should be noted that the image decompression engine **1200** uses the same components as the

image compression engine **303**, but is configured to receive a noise image **305** and hyperparameters **302**, and to output an approximated image I' **310**. As shown in the right-hand portion of FIG. **12**, a noise image N **305**, and alterable hyperparameters **302** of a neural network **1210**, are input into a processor **1230**. A processor **1230** is a common computing device used to process arithmetic and logical operations, and is commonly known in the art. A processor **1230** has two-way communication with at least a single bit of volatile memory **1240**, commonly known as Random Access Memory ("RAM"), for short-term storage of data to be accessed by a processor **1230**, the processor altering data in the RAM and using data in the RAM to alter its own processes. This is commonly understood as one of the key interactions in modern computing. A processor **1230** also communicates with a neural network **1210**, which operates as a function f in an algorithm **220**, operating as a framework for machine learning algorithms **1220** to process incoming data from a noise image **305** and, for the purposes of de-compression, the hyperparameters θ **302** of a previous neural network's compression of a goal image **304**. After hyperparameters θ **302** are input into a processor **1230**, the processor directs the neural network **1210** to incorporate and use these hyperparameters, directing the operation of the network as it transforms a noise image **305** into an approximation **310** of an input image **304**, using the algorithm **220** in FIG. **2**, the approximation image I' **310** being output to the network endpoint **307** for further use, including transmitting to a destination endpoint, saving on a hard-drive or external memory device, or other common uses for now uncompressed images.

FIG. **13** is a system diagram of an alternative embodiment of an image decompression engine **1310** arrangement being used for decompression while utilizing a specialized 2D convolution Application Specific Integrated Circuit ("ASIC") **1311**, according to an embodiment. It should be noted that the image decompression engine **1300** uses the same components as the image compression engine **309**, but is configured to receive a noise image **305** and hyperparameters **302**, and to output an approximated image I' **310**. As shown in the right-hand portion of FIG. **3**, a noise image N **305**, and alterable hyperparameters **302** of a neural network **1310**, are input into a processor **1330**. A processor **1330** is a common computing device used to process arithmetic and logical operations, and is commonly known in the art. A processor **1330** has two-way communication with at least a single bit of volatile memory **1340**, commonly known as Random Access Memory ("RAM"), for short-term storage of data to be accessed by a processor **1330**, the processor altering data in the RAM and using data in the RAM to alter it's own processes. This is commonly understood as one of the key interactions in modern computing. A 2D convolution ASIC **1311** also communicates bi-directionally with both the system processor **1330** and memory **1340**, in order to handle specialized processing of convolutional neural network **1310** data much faster than a general central processing unit might otherwise achieve. A processor **1330** also communicates with a neural network **1310**, which operates as a function f in an algorithm **220**, operating as a framework for machine learning algorithms **1320** to process incoming data from a noise image **305** and, for the purposes of de-compression, the hyperparameters θ **302** of a previous neural network's compression of a goal image **304**. After hyperparameters θ **302** are input into a processor **1330**, the processor directs the neural network **1310** to incorporate and use these hyperparameters, directing the operation of the network as it transforms a noise image **305** into an approximation **310** of an input image **304**, using the algorithm **220** in FIG. **2**, the approximation image I' **310** being output to the network endpoint **307** for further use, including transmitting to a destination endpoint, saving on a hard-drive or external memory device, or other common uses for now uncompressed images.

Because training of a single neural network to effectively map a known noise image to a desired image typically takes a highly-optimized graphical processing unit (GPU)-based machine many hours to accomplish for each desired image to be compressed, using normal training methods based on (for example) steepest gradient descent), it is crucial to find a different way to efficiently determine the weights of f for a given desired image. According to an aspect, the inventors have determined that it is possible to generate weights for f, to arbitrary accuracy (in the sense of how closely an output image obtained by applying N to f matches the input image used to generate the respective weights of f), in a single pass through a metanetwork described below. Specifically, by passing the desired image I and the known noise image N as inputs to a function g using a metanetwork, the weights for fare obtained in a single pass, as described below with reference to FIGS. **14-17**. More precisely, the inventors have shown that a metanetwork arranged as shown in FIG. **17** demonstrated a massively increased encoding efficiency with regards to runtime compression of images. Specifically, training via SGD on high-end GPU's took more than 6 hours. In contrast to that, the runtime of g is less than a second on similar hardware, and can be less than 100 milliseconds if specialized hardware (such as hardware-based optimized convolution stages).

FIG. **14** is a system diagram of high-level components used in the operation of a system using a metanetwork to achieve image or video compression, and decompression, according to a preferred embodiment. As shown on the left of FIG. **14**, a given goal image I **304** is provided to a metanetwork engine **1410**, alongside a static (that is, known and unchanging) noise image N **305**. Metanetwork engine **1410** comprises a "network of neural networks", including multiple single neural networks that each perform processing on a portion of the goal image I **304**, such as specific features or color spectra (for example, in a three-network metanetwork, each network may focus on one of each of the red, blue, and green color bands within the image). Metanetwork engine **1410** uses convolutional training between the single networks within it to arrive at the set of hyperparameters **302** that are appropriate for any given image decompression engine **309** to reconstruct the goal image **304** (or an arbitrarily-similar recreation thereof) from the noise image **305**. This set of hyperparameters **302** may then be stored for repeated future use, for example to enable many clients to reconstruct the goal image **304** from a single set of calculated hyperparameters (for example, as may be useful for a photo or video streaming service, wherein the same content is sent repeatedly to a large number of destinations), and may be sent via a network **306** from one endpoint **301** to another **307**. At the network destination, the received set of hyperparameters **308** are then provided to an image decompression engine **309** as input along with the noise image I **311**, so that the image decompression engine **309** may produce a reasonably-close recreation of the goal image, the recreated image being denoted as I' **310**.

FIG. **15** is a system overview diagram of a metanetwork engine **1410**, used to train a metanetwork with a set of training images, and used to compress and find filters that may be used to transform a noise image into an approximation of an input image, according to a preferred embodiment.

According to the embodiment, a given goal image I **304** is provided to a metanetwork engine **1410**, alongside a static noise image N **305** as inputs. Metanetwork engine **1410** comprises a processor **1540** and memory **1559** for performing the machine learning tasks associated with the training and transformation processes. A neural network **1510** trains on a set of training images **1530** using machine learning algorithms **1520** to arrive at an appropriate set of hyperparameters for operation, the hyperparameters comprising the set of hyperparameters necessary for the metanetwork engine **1410** to create a set of alterable hyperparameters **302** to store and transmit to target image encoding networks, given the inputs of N **305** and I **304**. In other words, the set of hyperparameters determined through training is the set used for operation of the metanetwork, and said operation (when given the correct, trained set of hyperparameters) then produces the desired set of hyperparameters **302** from the noise **305** and target **304** images.

FIG. **16** is a dataflow diagram of a system **1610** for lossy compression utilizing a metanetwork **1602** to train, compress, and send data for decompression to a system utilizing a specific neural network configuration **1640**, according to an embodiment. According to the embodiment, metanetwork **1602** instantiates a function g, wherein g, when given a known noise image **1603** and an original image **1601** as inputs, determines a specific set of hyperparameters **1604** for the given original image I **1601** and noise image N **1603** as inputs. The hyperparameters **1604** have the property that, when inserted (for example, at a destination device) as weights into a neural network to define a specific instance of a decompression function f **1640**, which can be used to map the same known/static noise image **1630** (here, "the same" means noise image **1630** is the same image as noise image **1603** used as input to gin metanetwork **1602** to produce hyperparameters **1604**. According to a preferred aspect, hyperparameters **1604** may be transmitted to a destination image encoding network **1640**, which comprises a function f such that (produces a facsimile of the original image I, dubbed I' **1650**, given the noise image N **1630** and hyperparameters **1604** as inputs. Stated mathematically, this operation takes the form of the set of functions **1620**:

Given: $\{I1, \ldots, IK\}$, N, ε, f

Find: g

So that for $j=\{1, \ldots, K\}$: $g(Ij, N):=\theta'j$

$f(g(Ij, N)|N):=I'j$

$h(I'j, Ij)\leq\varepsilon\Leftrightarrow h(f(g(Ij, N)|N), Ij)\leq\varepsilon$

FIG. **17** is a system diagram of multiple individual neural networks **1710***a* communicating with each other within a metanetwork **1710** to produce a plurality of sets of filter weights **1721**, **1723**, **1725**, which may be inserted into neural networks **1722**, **1724**, and **1726**, which collectively embody a specific instance of function f that may be used to map noise image **1701** to image **1730**, which is close—to within an arbitrary error limit—to identical to input image **1711**. As shown, a metanetwork **1710** is a network of neural networks, comprising a plurality of individual networks that each perform independent machine learning tasks focused on a portion of an original image **1711**. As shown, one arrangement uses three individual networks (and the inventor has determined through practice that this configuration provides excellent performance for the relative amount of resources utilized, reducing an image compression task from hours to milliseconds), however alternate metanetwork arrangements are possible according to the embodiment such as using only two individual networks, or using four or more individual networks.

When an original image **1711** is provided as an input to an individual network **1710***a* (while only this specific individual network is highlighted within the figure, this was done for the sake of clarity and it should be appreciated that the discussion of operation of **1710***a* applies to any and all individual networks present in the metanetwork **1710**), a sequence of convolutional filters **1714***a-n* are applied, wherein the output of each filter may be provided as an input to the next, to enable machine learning. Each individual network's convolutional outputs may also be provided as inputs to the next sequential filter in another individual network's processing **1712***a-n*, **1713***a-n*, so that the networks effectively learn from each other's processing and collectively "zero in" on ideal solutions. After this convolutional processing, a number of non-convolutional final filters **1715***a-n*, **1716***a-n*, **1717***a-n* may be applied to each individual network's output (and in this case, only that network's output), using the static noise image **1701** as an added input.

This produces a set of filters **1721**, **1723**, **1725** that are based on the combined development of the convolutional, collective processing of the original image, as well as the network-specific processing based on the noise image, such that each filter is different (being based on only a single network's processing, and therefore varying from one another due to variances in the networks and their respective outputs and learning processes), but the combination of filters, when applied in sequence at a target image encoding network **1720**, reconstructs successively more-accurate representations **1722**, **1724**, **1726** before arriving at a final, arbitrarily-similar reconstruction **1730** of the original image **1711**.

It will be seen, in FIG. **17**, that data is passed between layers within a given convolutional neural network (e.g., **1712***a-n*), as is conventional. But additionally, inter-metanetwork connections are made, according to an aspect, linking outputs of one neural network (one horizontal row) of a metanetwork (for example, **1712***a-n*) to the input of a next stage of a different neural network (a different horizontal row, such as **1713***a-n*), as shown in FIG. **17**. During some initial tests of multiple metanetworks without these inter-metanetwork connections, training and quality challenges were encountered. The training challenge was the vanishing gradient problem. This occurs when the updates the learning algorithm wants to make to the weights become extremely small (in the order of 10^{-8}) due to continuous multiplications by small values. These small updates result in a network which becomes "stale" and stops learning; in other words, the function stops improving. As done in intra-metanetwork connections, this problem may be fixed by adding skip connections in between the layers within a metanetwork to shorten the route an update has to take to get to its parameter, lowering the order by which the update diminishes. This technique was fully utilized in an exemplary aspect, with substantial improvements noted.

To further improve the flow of information, inter-metanetwork pathways are added. These act as information-injections between the metanetworks. Their main role is to update the current metanetwork on the state of the previous ones. This further helped the flow of gradient information during training, leading to a training process that is more stable while requiring less time.

Another reason for adding inter-metanetwork pathways is so the current metanetwork may be aware of the filter (and therefore transformation) the previous network produced, and it may produce it's filter in a way that will complement the transformation of the previous filter rather than cancel it

out. This ability to know the state of the previous metanetwork is important since in image encoding networks according to aspects of the invention, the transformations to the input (noise) are typically applied in order. Therefore, if a metanetwork is tasked with predicting a transformation at a particular stage, it should know the previous transformations that have already been applied, in other words, the state of the previous metanetwork rows.

Each metanetwork is tasked with predicting the filter which will most adequately transform an image-encoding network input to a step closer to a desired image. The input to the metanetwork is just the desired image (the known noise image is injected late in the first row at layers **1715***a-n*, as shown in FIG. **17**), so the metanetwork is seeing an incomplete picture. It does not see the "from" image but just the "to" image. Hence, a late fusion of the IEN input (noise) is provided to the metanetwork. This increases the information the metanetwork can use to make its prediction, and gives a boost in image quality. Furthermore, this fusion of information is done in an "or" manner, so the metanetwork can choose if it requires it or not.

To summarize, a method according to an aspect, such as that shown in FIG. **17**, may be viewed as an ensemble of metanetworks, since the method uses a collection or group of metanetworks. One might argue that it's the same network; however, this is false since all individual metanetworks are independent from one another with regards to their trainable parameters, inputs and outputs. It is not even necessary to train them together, but it is convenient.

Metanetwork **1710** must be trained before it can carry out its function of determining the weights **1722**, **1723**, **1725** required for function f to map noise image N **1701** to target image **1730**. Accordingly, FIG. **18** is a method diagram illustrating steps required for training metanetwork **1710** for use in lossy compression of images and video using a metanetwork. In an initial step **1810**, a set of training images j are provided to a metanetwork as inputs. These are used to train the metanetwork based on the images j and a given noise image N **1820**. This training, as described above in FIG. **15**, arrives at a set of filters needed to apply to the noise image N to arrive at a reconstruction of a given original image I **1830**. In more detail, this reconstruction process involves a number of individual networks within the metanetwork, each of which generates a subset of hyperparameters **1840**, and each of which subset is different from the others and focused on a specific portion or attribute of the input image I **1850**. Each subsequent individual network takes, as input, the states of all previous networks **1860** so that their collective machine learning is used as a convolutional neural network built out of smaller, more specialized convolutional neural networks (each being focused on a specific attribute of the image, while the overall metanetwork being focused on the whole by using each specific network as a convolutional filter within its own processing). To reconstruct the target image, static image N is passed through the successive filters developed by the networks **1870**, producing a close approximation image I' **1880**. When the approximation image is determined to be acceptable, that set of hyperparameters is stored and training is considered complete; the hyperparameters may then be sent **1890** to any arbitrary number of destination image encoding networks, each of which may then use the hyperparameters and noise image N to rapidly produce the reconstructed image I'.

FIG. **19** is a flowchart of the steps taken for a single network within a metanetwork to train on a set of images and produce a network operating as a portion of function g, for neural network hyperparameter prediction of an image encoding network f, according to an embodiment. In an initial step **1901**, a set of training images j is input to the metanetwork. At each individual network within the metanetwork, a check is performed **1902** to determine if a noise image is present. If no noise image is present, one is provided **1903**, and then (or if the noise image was already present) the metanetwork executes the image transformation function g on each of the training images j_n **1904**. After performing the transformation, the result is checked to determine whether the output image is acceptably close to a desired image I **1905**, and if not then each individual network within the metanetwork alters its parameters slightly **1906** and repeats the function g, to iterate closer to the desired output result. When the recreated image I' is acceptably close to the original I, the set of hyperparameters is stored as the acceptable set of hyperparameters needed for an acceptable image transformation **1907**.

FIG. **20** is a flowchart of the process of multiple networks communicating within a metanetwork for the purposes of cross-training and developing progressive filters to transform a static image with, to help alleviate the vanishing gradient problem, according to an embodiment. In an initial step **2010**, a convolutional processing layer i is executed across all single networks within a metanetwork. Then **2020**, a check is performed to determine if additional layers exist, waiting to be performed. If so, then each individual network sends, as output, the results of its respective processing layer i to be used as an input for all next networks' next convolutional layer, i+1 **2040**. Then, i increments **2050** and operation continues **2010**. When no more layers exist, convolutional processing concludes and each individual network then produces its respective filter **2030**, thereby producing the complete set of filters needed to recreate a target image from a noise image.

Hardware Architecture

Generally, the techniques disclosed herein may be implemented on hardware or a combination of software and hardware. For example, they may be implemented in an operating system kernel, in a separate user process, in a library package bound into network applications, on a specially constructed machine, on an application-specific integrated circuit ("ASIC"), or on a network interface card.

Software/hardware hybrid implementations of at least some of the aspects disclosed herein may be implemented on a programmable network-resident machine (which should be understood to include intermittently connected network-aware machines) selectively activated or reconfigured by a computer program stored in memory. Such network devices may have multiple network interfaces that may be configured or designed to utilize different types of network communication protocols. A general architecture for some of these machines may be described herein in order to illustrate one or more exemplary means by which a given unit of functionality may be implemented. According to specific aspects, at least some of the features or functionalities of the various aspects disclosed herein may be implemented on one or more general-purpose computers associated with one or more networks, such as for example an end-user computer system, a client computer, a network server or other server system, a mobile computing device (e.g., tablet computing device, mobile phone, smartphone, laptop, or other appropriate computing device), a consumer electronic device, a music player, or any other suitable electronic device, router, switch, or other suitable device, or any combination thereof. In at least some aspects, at least some of the features or functionalities of the various aspects disclosed herein may be implemented in one or more virtualized computing

environments (e.g., network computing clouds, virtual machines hosted on one or more physical computing machines, or other appropriate virtual environments).

Referring now to FIG. **21**, there is shown a block diagram depicting an exemplary computing device **10** suitable for implementing at least a portion of the features or functionalities disclosed herein. Computing device **10** may be, for example, any one of the computing machines listed in the previous paragraph, or indeed any other electronic device capable of executing software- or hardware-based instructions according to one or more programs stored in memory. Computing device **10** may be configured to communicate with a plurality of other computing devices, such as clients or servers, over communications networks such as a wide area network a metropolitan area network, a local area network, a wireless network, the Internet, or any other network, using known protocols for such communication, whether wireless or wired.

In one embodiment, computing device **10** includes one or more central processing units (CPU) **12**, one or more interfaces **15**, and one or more busses **14** (such as a peripheral component interconnect (PCI) bus). When acting under the control of appropriate software or firmware, CPU **12** may be responsible for implementing specific functions associated with the functions of a specifically configured computing device or machine. For example, in at least one embodiment, a computing device **10** may be configured or designed to function as a server system utilizing CPU **12**, local memory **11** and/or remote memory **16**, and interface(s) **15**. In at least one embodiment, CPU **12** may be caused to perform one or more of the different types of functions and/or operations under the control of software modules or components, which for example, may include an operating system and any appropriate applications software, drivers, and the like.

CPU **12** may include one or more processors **13** such as, for example, a processor from one of the Intel, ARM, Qualcomm, and AMD families of microprocessors. In some embodiments, processors **13** may include specially designed hardware such as application-specific integrated circuits (ASICs), electrically erasable programmable read-only memories (EEPROMs), field-programmable gate arrays (FPGAs), and so forth, for controlling operations of computing device **10**. In a specific embodiment, a local memory **11** (such as non-volatile random-access memory (RAM) and/or read-only memory (ROM), including for example one or more levels of cached memory) may also form part of CPU **12**. However, there are many different ways in which memory may be coupled to system **10**. Memory **11** may be used for a variety of purposes such as, for example, caching and/or storing data, programming instructions, and the like. It should be further appreciated that CPU **12** may be one of a variety of system-on-a-chip (SOC) type hardware that may include additional hardware such as memory or graphics processing chips, such as a QUALCOMM SNAPDRAGON™ or SAMSUNG EXYNOS™ CPU as are becoming increasingly common in the art, such as for use in mobile devices or integrated devices.

As used herein, the term "processor" is not limited merely to those integrated circuits referred to in the art as a processor, a mobile processor, or a microprocessor, but broadly refers to a microcontroller, a microcomputer, a programmable logic controller, an application-specific integrated circuit, and any other programmable circuit.

In one embodiment, interfaces **15** are provided as network interface cards (NICs). Generally, NICs control the sending and receiving of data packets over a computer network; other types of interfaces **15** may for example support other peripherals used with computing device **10**. Among the interfaces that may be provided are Ethernet interfaces, frame relay interfaces, cable interfaces, DSL interfaces, token ring interfaces, graphics interfaces, and the like. In addition, various types of interfaces may be provided such as, for example, universal serial bus (USB), Serial, Ethernet, FIREWIRE™, THUNDERBOLT™, PCI, parallel, radio frequency (RF), BLUETOOTH™, near-field communications (e.g., using near-field magnetics), 802.11 (WiFi), frame relay, TCP/IP, ISDN, fast Ethernet interfaces, Gigabit Ethernet interfaces, Serial ATA (SATA) or external SATA (ESATA) interfaces, high-definition multimedia interface (HDMI), digital visual interface (DVI), analog or digital audio interfaces, asynchronous transfer mode (ATM) interfaces, high-speed serial interface (HSSI) interfaces, Point of Sale (POS) interfaces, fiber data distributed interfaces (FDDIs), and the like. Generally, such interfaces **15** may include physical ports appropriate for communication with appropriate media. In some cases, they may also include an independent processor (such as a dedicated audio or video processor, as is common in the art for high-fidelity A/V hardware interfaces) and, in some instances, volatile and/or non-volatile memory (e.g., RAM).

Although the system shown in FIG. **21** illustrates one specific architecture for a computing device **10** for implementing one or more of the inventions described herein, it is by no means the only device architecture on which at least a portion of the features and techniques described herein may be implemented. For example, architectures having one or any number of processors **13** may be used, and such processors **13** may be present in a single device or distributed among any number of devices. In one embodiment, a single processor **13** handles communications as well as routing computations, while in other embodiments a separate dedicated communications processor may be provided. In various embodiments, different types of features or functionalities may be implemented in a system according to the invention that includes a client device (such as a tablet device or smartphone running client software) and server systems (such as a server system described in more detail below).

Regardless of network device configuration, the system of the present invention may employ one or more memories or memory modules (such as, for example, remote memory block **16** and local memory **11**) configured to store data, program instructions for the general-purpose network operations, or other information relating to the functionality of the embodiments described herein (or any combinations of the above). Program instructions may control execution of or comprise an operating system and/or one or more applications, for example. Memory **16** or memories **11**, **16** may also be configured to store data structures, configuration data, encryption data, historical system operations information, or any other specific or generic non-program information described herein.

Because such information and program instructions may be employed to implement one or more systems or methods described herein, at least some network device embodiments may include nontransitory machine-readable storage media, which, for example, may be configured or designed to store program instructions, state information, and the like for performing various operations described herein. Examples of such nontransitory machine-readable storage media include, but are not limited to, magnetic media such as hard disks, floppy disks, and magnetic tape; optical media such as CD-ROM disks; magneto-optical media such as optical disks, and hardware devices that are specially configured to

store and perform program instructions, such as read-only memory devices (ROM), flash memory (as is common in mobile devices and integrated systems), solid state drives (SSD) and "hybrid SSD" storage drives that may combine physical components of solid state and hard disk drives in a single hardware device (as are becoming increasingly common in the art with regard to personal computers), memristor memory, random access memory (RAM), and the like. It should be appreciated that such storage means may be integral and non-removable (such as RAM hardware modules that may be soldered onto a motherboard or otherwise integrated into an electronic device), or they may be removable such as swappable flash memory modules (such as "thumb drives" or other removable media designed for rapidly exchanging physical storage devices), "hot-swappable" hard disk drives or solid state drives, removable optical storage discs, or other such removable media, and that such integral and removable storage media may be utilized interchangeably. Examples of program instructions include both object code, such as may be produced by a compiler, machine code, such as may be produced by an assembler or a linker, byte code, such as may be generated by for example a JAVA™ compiler and may be executed using a Java virtual machine or equivalent, or files containing higher level code that may be executed by the computer using an interpreter (for example, scripts written in Python, Perl, Ruby, Groovy, or any other scripting language).

In some embodiments, systems according to the present invention may be implemented on a standalone computing system. Referring now to FIG. **22**, there is shown a block diagram depicting a typical exemplary architecture of one or more embodiments or components thereof on a standalone computing system. Computing device **20** includes processors **21** that may run software that carry out one or more functions or applications of embodiments of the invention, such as for example a client application **24**. Processors **21** may carry out computing instructions under control of an operating system **22** such as, for example, a version of MICROSOFT WINDOWS™ operating system, APPLE OSX™ or iOS™ operating systems, some variety of the Linux operating system, ANDROID™ operating system, or the like. In many cases, one or more shared services **23** may be operable in system **20**, and may be useful for providing common services to client applications **24**. Services **23** may for example be WINDOWS™ services, user-space common services in a Linux environment, or any other type of common service architecture used with operating system **21**. Input devices **28** may be of any type suitable for receiving user input, including for example a keyboard, touchscreen, microphone (for example, for voice input), mouse, touchpad, trackball, or any combination thereof. Output devices **27** may be of any type suitable for providing output to one or more users, whether remote or local to system **20**, and may include for example one or more screens for visual output, speakers, printers, or any combination thereof. Memory **25** may be random-access memory having any structure and architecture known in the art, for use by processors **21**, for example to run software. Storage devices **26** may be any magnetic, optical, mechanical, memristor, or electrical storage device for storage of data in digital form (such as those described above, referring to FIG. **21**). Examples of storage devices **26** include flash memory, magnetic hard drive, CD-ROM, and/or the like.

In some embodiments, systems of the present invention may be implemented on a distributed computing network, such as one having any number of clients and/or servers. Referring now to FIG. **23**, there is shown a block diagram depicting an exemplary architecture **30** for implementing at least a portion of a system according to an embodiment of the invention on a distributed computing network. According to the embodiment, any number of clients **33** may be provided. Each client **33** may run software for implementing client-side portions of the present invention; clients may comprise a system **20** such as that illustrated in FIG. **22**. In addition, any number of servers **32** may be provided for handling requests received from one or more clients **33**. Clients **33** and servers **32** may communicate with one another via one or more electronic networks **31**, which may be in various embodiments any of the Internet, a wide area network, a mobile telephony network (such as CDMA or GSM cellular networks), a wireless network (such as WiFi, WiMAX, LTE, and so forth), or a local area network (or indeed any network topology known in the art; the invention does not prefer any one network topology over any other). Networks **31** may be implemented using any known network protocols, including for example wired and/or wireless protocols.

In addition, in some embodiments, servers **32** may call external services **37** when needed to obtain additional information, or to refer to additional data concerning a particular call. Communications with external services **37** may take place, for example, via one or more networks **31**. In various embodiments, external services **37** may comprise web-enabled services or functionality related to or installed on the hardware device itself. For example, in an embodiment where client applications **24** are implemented on a smartphone or other electronic device, client applications **24** may obtain information stored in a server system **32** in the cloud or on an external service **37** deployed on one or more of a particular enterprise's or user's premises.

In some embodiments of the invention, clients **33** or servers **32** (or both) may make use of one or more specialized services or appliances that may be deployed locally or remotely across one or more networks **31**. For example, one or more databases **34** may be used or referred to by one or more embodiments of the invention. It should be understood by one having ordinary skill in the art that databases **34** may be arranged in a wide variety of architectures and using a wide variety of data access and manipulation means. For example, in various embodiments one or more databases **34** may comprise a relational database system using a structured query language (SQL), while others may comprise an alternative data storage technology such as those referred to in the art as "NoSQL" (for example, HADOOP CASSANDRA™, GOOGLE BIGTABLE™, and so forth). In some embodiments, variant database architectures such as column-oriented databases, in-memory databases, clustered databases, distributed databases, or even flat file data repositories may be used according to the invention. It will be appreciated by one having ordinary skill in the art that any combination of known or future database technologies may be used as appropriate, unless a specific database technology or a specific arrangement of components is specified for a particular embodiment herein. Moreover, it should be appreciated that the term "database" as used herein may refer to a physical database machine, a cluster of machines acting as a single database system, or a logical database within an overall database management system. Unless a specific meaning is specified for a given use of the term "database", it should be construed to mean any of these senses of the word, all of which are understood as a plain meaning of the term "database" by those having ordinary skill in the art.

Similarly, most embodiments of the invention may make use of one or more security systems **36** and configuration

systems **35**. Security and configuration management are common information technology (IT) and web functions, and some amount of each are generally associated with any IT or web systems. It should be understood by one having ordinary skill in the art that any configuration or security subsystems known in the art now or in the future may be used in conjunction with embodiments of the invention without limitation, unless a specific security **36** or configuration system **35** or approach is specifically required by the description of any specific embodiment.

FIG. **24** shows an exemplary overview of a computer system **40** as may be used in any of the various locations throughout the system. It is exemplary of any computer that may execute code to process data. Various modifications and changes may be made to computer system **40** without departing from the broader scope of the system and method disclosed herein. Central processor unit (CPU) **41** is connected to bus **42**, to which bus is also connected memory **43**, nonvolatile memory **44**, display **47**, input/output (I/O) unit **48**, and network interface card (NIC) **53**. I/O unit **48** may, typically, be connected to keyboard **49**, pointing device **50**, hard disk **52**, and real-time clock **51**. NIC **53** connects to network **54**, which may be the Internet or a local network, which local network may or may not have connections to the Internet. Also shown as part of system **40** is power supply unit **45** connected, in this example, to a main alternating current (AC) supply **46**. Not shown are batteries that could be present, and many other devices and modifications that are well known but are not applicable to the specific novel functions of the current system and method disclosed herein. It should be appreciated that some or all components illustrated may be combined, such as in various integrated applications, for example Qualcomm or Samsung system-on-a-chip (SOC) devices, or whenever it may be appropriate to combine multiple capabilities or functions into a single hardware device (for instance, in mobile devices such as smartphones, video game consoles, in-vehicle computer systems such as navigation or multimedia systems in automobiles, or other integrated hardware devices).

In various embodiments, functionality for implementing systems or methods of the present invention may be distributed among any number of client and/or server components. For example, various software modules may be implemented for performing various functions in connection with the present invention, and such modules may be variously implemented to run on server and/or client components.

The skilled person will be aware of a range of possible modifications of the various embodiments described above. Accordingly, the present invention is defined by the claims and their equivalents.

What is claimed is:

1. A system for lossy image and video compression utilizing a metanetwork, comprising:

a metanetwork engine comprising a processor, a memory, and a first plurality of programming instructions stored in the memory, wherein the first plurality of programming instructions, when operating on the processor, cause the processor to:

receive a desired image;

receive a noise image;

receive a set of training images;

using the set of training images, train a plurality of neural networks to reconstruct each of the set of training images by mapping the noise image to each of the set of training images;

store the parameters for each of the plurality of neural networks as a set of metanetwork hyperparameters;

use the set of metanetwork hyperparameters as operating parameters for each of the plurality of neural networks;

use the plurality of neural networks to map the noise image to the desired image, producing a second set of hyperparameters corresponding to the specific filters produced from the operation of each of the plurality of neural networks, such that the second set of hyperparameters, when applied to the noise image using the neural network, produce an approximation of the desired image within an error that is less than a pre-determined threshold; and

store the second set of hyperparameters for use in future image mapping operations.

2. The system of claim **1**, wherein each of the plurality of neural networks:

generates at least one convolutional filter, wherein the noise image may be filtered through all convolutional filters in succession, mapping it to an approximation of a desired image; and

facilitates communication between the plurality of neural networks to alleviate the vanishing gradient problem.

3. The system of claim **2**, wherein the plurality of neural networks may be located on separate computing devices, connected across a network.

4. The system of claim **1**, wherein the noise image is static and unchanging.

5. A method for lossy image compression utilizing a metanetwork, comprising the steps of:

receiving a desired image;

receiving a noise image;

receiving a set of training images;

using the set of training images to train a plurality of neural networks to reconstruct each of the set of training images by mapping the noise image to each of the set of training images;

storing the parameters for each of the plurality of neural networks as a set of metanetwork hyperparameters;

using the set of metanetwork hyperparameters as operating parameters for each of the plurality of neural networks;

using the plurality of neural networks to map the noise image to the desired image, producing a second set of hyperparameters corresponding to the specific filters produced from the operation of each of the plurality of neural networks, such that the second set of hyperparameters, when applied to the noise image using the neural network, produce an approximation of the desired image within an error that is less than a predetermined threshold; and

storing the second set of hyperparameters for use in future image mapping operations.

6. The method of claim **5**, further comprising the steps of:

Generating, at each of the plurality of neural networks, at least one convolutional filter, wherein a noise image may be filtered through the convolutional filters in succession, mapping it to an approximation of a desired image, using a plurality of neural meta-networks; and

facilitating communication between the plurality of neural networks to alleviate the vanishing gradient problem.

7. The method of claim **6**, wherein the plurality of neural networks may be located on separate computing devices, connected across a network.

8. The method of claim 5, wherein the noise image is static and unchanging.

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